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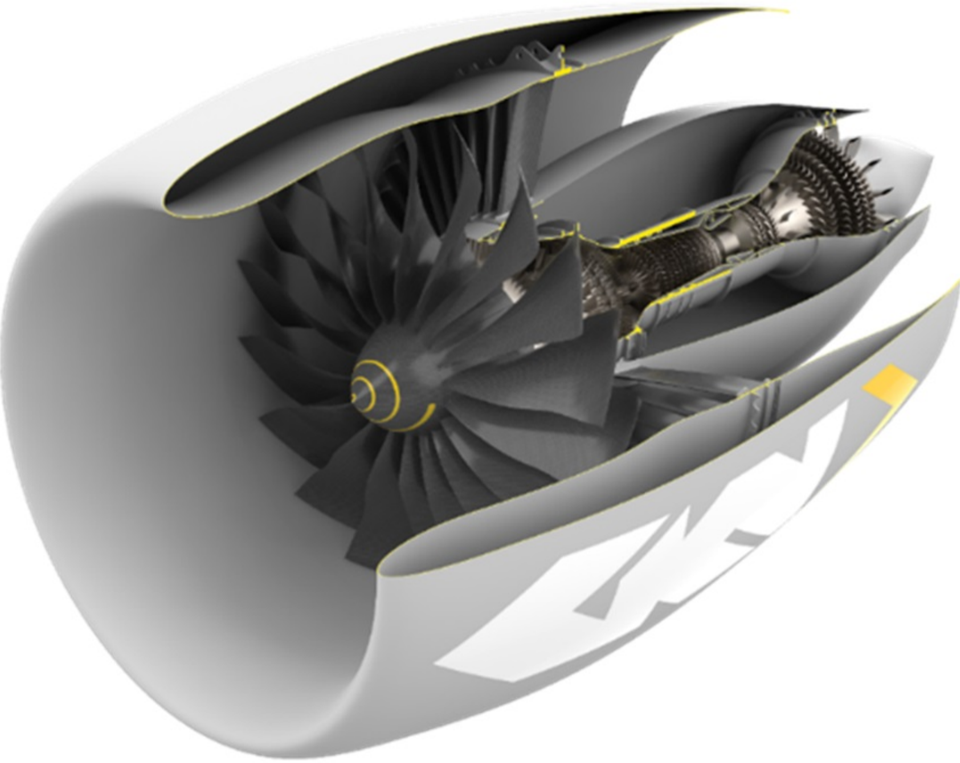

Uncertainties and Design Margins
A robust design approach for jet engine component design

Master's thesis in Product Development

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CHALMERS UNIVERSITY OF TECHNOLOGY
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Abstract

Aerospace industry is driven by the need to develop new concepts and methods to handle the constraints of weight and performance efficiency, reliability, regulatory safety compliance, and cost-effectiveness. In parallel to these demands, engineers have to manage increasing design complexity by using Multi Disciplinary models and accelerate the product development cycles to be able to fulfil the market demands.

To achieve high performing, robust and sustainable product design, a more informed management of design margins is required that minimizes or reduces the uncertainty. First part of study has employed a qualitative methodology where interviews have been conducted with experienced engineers. The interviews have focused the understanding and practical experience on use of design margins, uncertainty quantification. Furthermore, feasibility of adopting probabilistic tools in their day-to-day engineering workflows have been asked. The data gathered through the interview study has been analyzed and presented in AIM diagrams to establish the case for a computational study. It has been observed that the decisions on design margins are implicit and not in detail recorded, but are following previous design practices connected to the area. These challenges are addressed by in the second part of the study, where a generalized probabilistic framework are used into the existing design-analysis environment at GKN. In this work it is realized by using the workbench of ANSYS OptiSLang, which contains a workflow including sensitivity analysis to be able to assess parameters influence to the response, a deterministic design optimization to find the optimal combination of values for parameters. This can be finalized by robustness and reliability analysis to ensure the considered design satisfies the user defined robustness criteria expressed in terms of six sigma. The scope of the thesis further extents to show that robustness analysis can also be studied by integration of the mathematical framework of Probabilistic VMEA (variation mode and effect analysis) into the workflow of ANSYS OptiSLang. This integration is a challenge as well as an opportunity to make a more efficient algorithm for robustness analysis. In this study, a steel hook and a simplified steel lug (used in aerospace engines) have been used to illustrate the methodology with comparative results as well as showing the opportunities by using Probabilistic VMEA.

Division of work

The work carried out in this thesis has been evenly divided between both authors. A significant portion of the practical activities such as data collection, conducting and transcribing interviews, and participating in workshops were carried out collaboratively to ensure consistent interpretation and shared insights across both areas of expertise.

To facilitate an effective and manageable writing process, the responsibility for different chapters and sections was divided between the two authors, allowing individual reflection and focused analysis. The division of sections is as follows:

- Kevin (Quality and Operations Management) - Chapters 1, 2 and Sections 3.1, 3.2, 3.3 in Chapter 3.

- Sandeep: Chapter 3 :3.4, 3.5, Chapter 4, Chapter 5, and Chapter 6.

Despite the division of responsibility, the overall framework and structure of the report were jointly planned at the beginning of the thesis work. This collaborative planning supported by supervisor guidance both from the university and the industrial partner ensured coherence in both tone and approach.

This division was intentionally structured to reflect the interdisciplinary nature of the project, combining insights from Quality and Operations Management and Product Development to gain a broader and more integrated understanding of the research topic.

Acknowledgements

This master's thesis was conducted during the spring of 2025 at GKN and comprised of 30 credits. The project took place in the Industrial and Materials Science department at Chalmers University of Technology, marking the final project of the two-year studies in the Master's program Product Development and Quality & operations management. We extend our gratitude to GKN for their invaluable support throughout the project. Special thanks to Pär Nordström and our GKN supervisor, Sören Knuts for their expertise, time, and for giving us the opportunity to undertake the thesis at GKN. We are also grateful to all the employees at GKN who assisted us and took part in the interviews, showing great willingness to help for this project. We would like to acknowledge our examiner Ola Isaksson and supervisor at Chalmers, Arindam Brahma. We are thankful for your input and feedback throughout this master thesis journey. Your knowledge and guidance have been instrumental in helping us complete our thesis work while enhancing our understanding of the subject matter.

Sandeep Santhosh,Sanjeeth Kevin Raja, Gothenburg, june 2025

List of Acronyms

Below is the list of acronyms that have been used throughout this thesis listed in alphabetical order:

AM	Additive Manufacturing
CAD	Computer Aided Design
COP	Coefficient of Prognosis
CoV	Coefficient of Variation
CTQ	Critical To Quality
DFSS	Design for Six Sigma
DMADV	Define, Measure, Analyze, Design, and Verify
DMADOV	Define,Measure, Analyze, Design, Optmize and Verify
DMAIC	Define, Measure, Analyze, Improve, Control
DOE	Design Of Experiments
FEA	Finite Element Analysis
FMEA	Failure Modes and Effects Analysis
MDO	Multi Disciplinary Optimization
MCS	Monte Carlo Simulation
MOP	Metamodel of Optimal Prognosis
MPa	Mega Pascal
OEM	Original Equipment Manufacturer
QA	Quality Assurance
QFD	Quality Function Deployment
RBDO	Reliability Based Design Optimization
RDM	Robust Design Methodology
RDO	Robust Design Optimization
RPN	Risk Priority Number
RQ	Research Question
RSS	Root Square Sum
STD	Standard Deviation
UQ	Uncertainty Quantification
VMEA	Variation Mode and Effect Analysis

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Introduction

1.1 Background

Engineering teams across various functional departments in the aerospace sector cope with lot of challenges to design components that are structurally reliable, cost efficient, and they need to be optimized for best performance [[1]]. These expectations have to be addressed, despite a rise in system complexity, tighter environmental regulations, and uncertainty in geopolitical situations, which necessitate new techniques like robust design, sustainable quality management, and smart manufacturing to deliver products as per the market timelines [[2]].

In this context, the ability to make well informed design decisions early in the development process has become crucial [[3]]. What sets high for the engineering teams to perform is not only their technical ability but their skill to account for uncertainty and margin application, while still progressing through demanding development cycles in product development [[4, 5, 6]]. Traditionally, the aerospace industries practise the deterministic design methods and models for developing airworthy systems and components [[7, 8, 9]]. These models evaluate performance under the fixed assumptions for loads, geometry, and boundary conditions. Further, to handle the unknowns, industries have historically added conservative safety margins [10, 11]. While this approach has proven to be effective in preventing catastrophic failures on a consistent basis for centuries, it sometimes results in over engineered parts that are heavier, become more expensive, or often unnecessarily constrained. Nevertheless, this legacy approach has been continuously adopted by companies because it offers predictability, but at the cost of flexibility, optimization and traceability.

Recent literature reviews have highlighted the limitation of deterministic mindset thinking in modern engineering design [[10, 11]]. Eckert et al., have noted that small geometric deviations, unnoticed boundary condition shifts, or material property fluctuations can significantly alter a component's mechanical behaviour under load [[12]]. These variations are rarely captured in early-stage models, which lead to discrepancies between simulated and real-world conditions. Eckert et al., have also emphasized that engineers in the absence of structured tools for uncertainty modelling will attempt to use implicit safety margins without formal documentation [[13]]. These undocumented assumptions definitely create knowledge gaps that affect validation, redesign, and handover processes.

The shift towards digitalization and model-based system engineering has helped many organizations like GKN Aerospace to systematically organise their workflows and improve collaboration among various design teams to meet the customer's satisfaction. Nevertheless, the challenges of managing uncertainties have not been yet fully resolved. Therefore, use of probabilistic design methods is to be explored, to develop the uncertainty knowledge-based robust design solutions, besides meeting the certification requirements.

In this thesis, we address this by managing uncertainties and variations in the early stages of design process. The focus is laid on the design of structural components for jet engine, which the GKN engineering teams have been working at TröllHattan, Sweden. Though these components appear simple in geometry, but are very sensitive to fatigue, stress concentration and installation alignment.

1.2 GKN Aerospace

GKN Aerospace is a renowned global leader in the manufacturing sector of the aerospace industry and supply chain, delivering advanced composite & metallic jet engine components for civil aircraft and spacecraft. With a broad portfolio that includes fuselage structure, engine components, and aerostructures, GKN operates across more than a dozen countries and collaborates with major commercial OEM projects with companies like Airbus, Boeing and Rolls Royce.

In recent years, GKN Aerospace has been pursuing digital transformation strategy, in order to improve design traceability, data integration, and simulation efficiency [[11, 12, 13, 14]]. The adoption of digital platforms integrates the activities like design, stress analysis and manufacturing teams under common standards and environments. Initiatives such as Quality Management System (QMS) has formalized the product development phases, by centralizing the processes like engineering workbench, technical documentation and design certification. This integrated approach allows for efficient reuse of models, consistent design updation and validation, a structured communication of uncertainties, and informed design margins across different functional teams.

1.2.1 QMS- Quality Management System

The QMS at GKN Aerospace is designed to provide a formalized structure for managing their engineering activities throughout the complete life cycle of their product development process. It defines a sequence of maturity levels, each with specific technical deliverables and validation checkpoints. This system ensures that the design efforts proceed in a logical and traceable manner and also ensuring cross functional collaboration across various technical fields before moving on to the developmental stages. The QMS supports everything from initial concept definition to final product release, offering a framework for planning, monitoring and controlling the technical progress.

The value of QMS lies in its ability to enforce procedural discipline and stringent accountability. By setting clear objectives for each phase of the product development, the system reduces the likelihood of skipped steps, unrecorded assumptions or overlooked risks. At each gate, engineers are required to provide design models, validation results and risk assessments, before moving forward. This staged approval process encourages systematic thinking and supports company's goals for quality and safety compliance. However, the system also has its limitations, when applied to complex design environments that deal with uncertainties such as economic disruptions, geopolitical tensions and instability in supply chain etc.

QMS is primarily oriented toward procedural checks and documentation of results rather than a detailed exploration of design variation. Many assumptions such as fixed load conditions, nominal design geometry, or boundary simplifications are accepted during the early stages without being challenged or quantified for robustness [[13]]. These assumptions are rarely documented with sensitivity justifications and conservatism of the safety factor thereby making it difficult to revisit or adjust them later. Several researchers have reported these gaps in industrial process frameworks [[11, 12, 13, 14, 15, 16]].

1.2.2 Design Process

The design processes in GKN Aerospace are well organized and structured to develop airworthy components. It begins with capturing the requirements of a component, then to concept development stage, advancing to detailed design phase, subsequently manufacturing and design validation by physical test, leading to delivery of airworthy component (refer to Figure 1.1). This stage wise approach is intended to ensure that all the critical decisions are made with technical clarity and authority, considering all the known risks that are managed at appropriate points in the process. In fact, it is seen that each phase is carried out as per the company's QMS and is supported by digital tools, which allow the teams from various departments to collaborate with ease and efficiency.

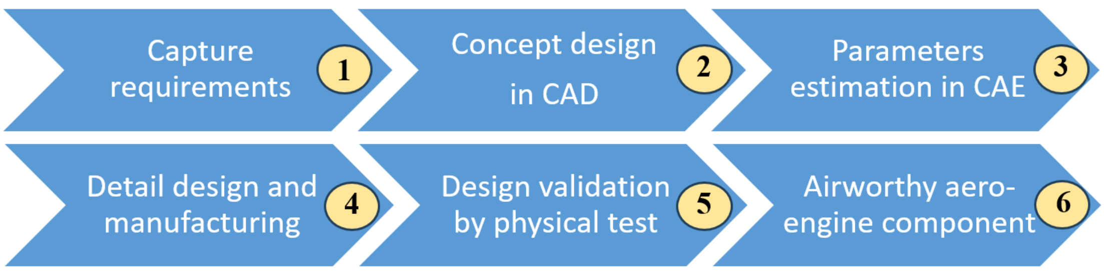


Figure 1.1: Design sequence of airworthy component

The process typically starts with the translations of customer needs in terms of engineering requirements and constraints such as load cases, performance metrics and geometric envelopes. Engineers then create specific design models, according to customer's requirements and use CAD and CAE tools to perform early simulations to validate the stress behaviour and asses the feasibility and reliability of the designed component, regarding real world conditions. As the design progresses, more detailed simulations will be conducted, including fatigue life analysis and manufacturing tolerances. However, these evaluations are done usually based on specific input values such as nominal dimensions or design limit loads (DLL).

The deterministic approach simplifies the design process but it is unclear about the effects of variations in real world conditions [[11, 12, 13, 16]]. Parameters such as bolt preloads, material anisotropy or geometric tolerances are often neglected or handled through conservative safety factors. While this strategy offers margins against risk, it also adds mass to the designed components, increasing the overall cost and sometimes complicating the certification in the long term. More importantly, the rationale behind these margins may not be really documented, making it difficult to justify or modify them in the later stages.

Relevant literatures support these observations [[11, 12, 13, 16]], because deterministic modelling is still a vigorous and dominating method in many engineering organizations, despite the availability of probabilistic approaches. Also, it is evident that engineers mainly rely on implicit knowledge and past experiences gained, while defining margins, which limits the repeatability and transparency of the design process [[17]]. Cronholm has discussed that, when uncertainty is not addressed systematically, the engineering teams may miss the opportunities for optimization and eventually end up in redesign [[18]].

Variation Mode and Effect Analysis (VMEA) is a probabilistic approach, which can identify variations in the critical parameters that affect the robustness of the designed component. By applying this method in early-stage design evaluations, engineers can build models that will reflect not only the desired nominal conditions but also its potential deviations. This enhances the confidence in robustness and reduces the reliance on undocumented safety provisions and unaccounted uncertainties [[19, 20]].

1.2.3 Preliminary Design

The preliminary design phase marks a critical transition between conceptual thinking and detailed engineering execution. In the context of GKN Aerospace, this phase serves as the foundation upon which stress analysis, manufacturing evaluations and fatigue assessments are built. It is during this phase that engineers begin to assign numerical values for the abstract constraints, arriving the basis for technical justifications. Although the models at this stage are typically simplified, they carry a significant weightage. Assumptions made during the preliminary design are often propagated through later stages, making it essential that they are both well founded and traceable.

At GKN Aerospace, the preliminary design phase typically involves creating a CAD based geometry that reflects the customer requirements of their interfaces and functional intentions of the component. Engineers define the load cases, boundary conditions and material choices and begin running Finite Element Analysis (FEA) to evaluate the basic stress distributions. These simulations are used to determine, whether the pre-defined concept meets its structural requirements and to identify regions of concern such as stress concentrations, buckling risks or areas with high fatigue sensitivity. Despite the availability of simulation tools, this phase still relies heavily on fixed nominal values, not seriously considering uncertainty in loads and material data, fatigue allowable and severity in operational conditions [[13, 19]].

Within the GKN's internal workflow process, the QMS outlines the specific maturity targets and documentation standards, available either from their customers (Original Equipment Manufacturer: OEMs) or as per the industry regulatory standards such as Federal Aviation Regulations (FAR) and Military Standard (MIL-STD) for the preliminary design stage [[21, 21, 22]]. These include finalized geometric definitions, justifications for the chosen load paths and initial verification through simulation. However, the intensity of these justifications can vary between the projects. In many of the cases, decisions are taken based on legacy designs or historical data and sometimes from previously recorded experiences. Nevertheless, the reasoning behind certain tolerances or load assumptions aren't formally accounted or recorded. This makes it difficult for others, namely manufacturing, verification or certification teams to understand the real intent behind these key design choices.

To overcome these traditional practices, advanced robust design method is required, in which the sensitivities of design parameters are captured and documented earlier in the project by applying a suitable probabilistic method. This makes the design iterations or optimization cycles as minimum. Subsequently, the fatigue life can be estimated in a robust manner with a better reliability index (quality), so that the design achieves digital manufacturing economical, producing large numbers in lesser time. Indeed, GKN moves ahead with such goals, to adopt digital twin technology.

1.2.4 Engineering Workbench (EWB)

The inhouse established workbench at GKN supports all the design activities throughout the product development life cycle. It brings together multiple tasks such as design, stress analysis, materials and manufacturing into a shared environment, where data, models and decisions are captured in a structured and traceable format. The integrated workbench facilitates the workflow like Design of Experiments (DOE), CAD modelling, FEA (CAE), documentation and reporting, ensuring that the technical information is accessible and version controlled, across their global teams. This approach is closely aligned with company's QMS, thereby providing engineers to navigate development phases with consistency and transparency. Figure 1.2 present a typical view of work steps involved in EWB.

The workbench plays a pivotal role in managing the complex interfaces and multi-functional inputs, which are very common in aerospace structural components. It allows engineers to build, modify and evaluate any geometry in a controlled manner, by setting the computational runs with defined boundary conditions and loads.

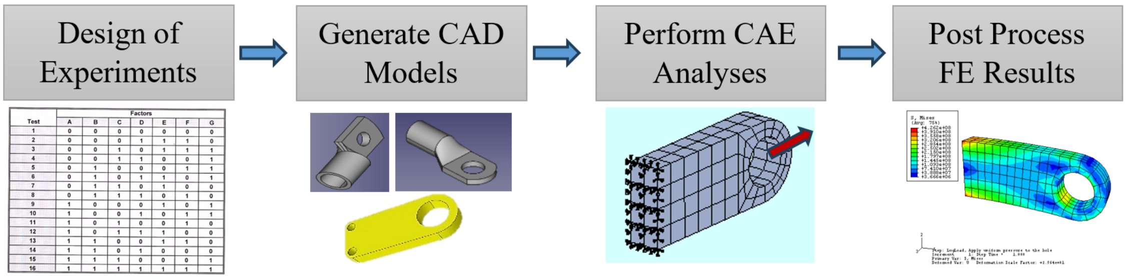


Figure 1.2: Schematic view showing current work steps in EWB

Further, the stress results are stored and documented for assessments like strength and buckling criteria and fatigue point of view. In spite of these merits, the current EWB operates primarily with deterministic methods. Most simulations conducted through this platform are based on fixed nominal values for loads, geometries and material properties. While this simplifies modelling procedure and reduces computational burden, it poses limitations on the ability to explore the effects of uncertainty in real world conditions.

Engineers are in general expected, not only to deliver the functional designs but also to explain and defend their decisions. Future aerospace products require many complex systems, optimally lighter airframe, and high-performance engines. Aviation industries are continuously looking for novel design methods and advanced systems to develop faultless flight vehicles, which can fly anywhere globally with lower operational cost [[2, 23]]. Towards this goal, we want to study application of probabilistic approach in the existing Engineering Workbench at GKN, which has already laid the foundation by bringing data, modelling, and certification into one environment to enhance and simplify the design process. Such integration provides data traceability and a friendly workflow for the engineers. One such study was carried out by Lebjioui, where application of Variation Model and Effect Analysis (VMEA) to Volvo GTT automotive industry was explored [[24]]. The sensitivity is assessed without an intensive probabilistic analysis to capture the design margins in terms of buffer and excess with respect to various geometric truck variants.

1.3 Aim & Research Questions

The primary aim of this thesis work is to explore, how engineering teams across various functional departments in GKN can better understand and manage the design margins with respect to uncertainties during the early development stage of product development. The focus here is to identify the various challenges and limitations in the current industrial design practices and investigate, whether a probabilistic approach like VMEA can enhance the robustness and trace the uncertainty and variations in the most sensitive design input parameters. The vision is set to devise a hybrid approach by introducing the probabilistic analysis into the traditional deterministic design method, so that the existing engineering workbench is able to handle a complex structural design without much complications.

This research further aims to examine the VMEA method for visualizing and analysing the parameter variation, how it affects the component's behaviour, in relevance to GKN's Engineering Workbench or broader design process. The purpose here is to support the engineers to identify the critical design variables, specifically to know that, which variation significantly affects the desired performance. Furthermore, a basis will be arrived according to evidence observed to justify the design margins with proper documentation, without requiring very intensive simulation efforts or disrupting established product development routines.

Aims:

- This research aims to apply the probabilistic VMEA method for visualizing and analysing the parameter variation, how it affects the component's behaviour, in relevance to GKN's Engineering Workbench or broader design process.
- Further, a structural design strategy will be arrived based on robust analysis and the evidences observed to justify the design margins with proper documentation, without requiring very intensive simulation efforts or disrupting the established product development routines.

To achieve these aims, a very specific objectives are proposed along with the research questions in section 1.3.1.

1.3.1 Problem Statement and Objectives

The aerospace industry has inherently depended on conservative engineering practices to ensure safety and reliability [[7, 8, 9, 25, 26]]. Generally, design margins are arrived with additional allowances to account for unknowns, variations and potential deviations from nominal performance. These margins are typically introduced early in the design process and carried through final validation, often without a detailed explanation of their origins or necessity. While this strategy minimizes the risk, it can also result in inefficient design, increase in overall weight and a higher production cost. More importantly, the rationale behind these safety margins remains undocumented, leaving critical gaps in the traceability and thereby hinder the opportunities for improvement.

At GKN Aerospace, the design of their jet engine components begins with a deterministic evaluation of structural performance. Engineers rely mainly on fixed value for boundary conditions, material properties and load cases, assuming ideal geometries and nominal scenarios. While this allows for rapid simulation and early phase feasibility checks, it doesn't adequately reflect the uncertainty and variations present in real world conditions. Factor such as misalignment during assembly, material inconsistencies or unexpected load fluctuations are rarely modelled in early stages, instead they are compensated for using a more generalized safety margin.

Although these safety buffers often succeed in preserving reliability, they are not always optimized. In some cases, they are overly conservative, leading to a more heavy and expensive components than deems necessary because the design considers unexpected failure risks. This inconsistency stems from a lack of structured variation modelling during initial design phase. Furthermore, this decision on the margin application is rarely documented, later other teams like manufacturing, certification and validation, struggle to understand the original design intent. This may lead to rework, inefficiency and primarily a disconnection between the simulation results and actual behaviour of the designed components.

The absence of structured tools for exploring parameter sensitivity also limits the potential for design optimization. Without understanding how input variability affects output behaviour, engineers today cannot confidently prioritize design improvements nor justify the inclusion or removal of specific safety factors. Existing CAE tools that perform FEA and probabilistic design tools like OptiSLang are capable of performing statistical evaluations but they are applied at a later stage in the process and requires significant setup, licenses and computation system capability to perform these calculations. Therefore, the present thesis aims to study the engineering design workflow from robustness perspectives, addressing the following research questions as objectives.

RQ1: What are the current industrial challenges at GKN related to the design processes in regards to the use of design margins?

RQ2: What is the process of working with design margins and robustness at GKN and how can it be improved?

These questions form the basis for us to perform both the qualitative study, consisting of 11 interviews in total with engineers from various functional teams and a computational study that explores, how VMEA integrated into OptiSLang can be used in design practice. Together these studies are focussed to identify the practical gaps in the current design approach and assess the feasibility of what value VMEA can add to the deterministic design paradigms.

1.4 Delimitations

The present thesis specifically focuses on the challenges surrounding uncertainty and the application and management of design margins during the early stages of mechanical design process at GKN Aerospace. This study limits its scope to one organizational context and a specific subset of design activities, related to structural components.

While the relevant articles and industrial studies are reviewed from open literatures to formulate the problem and support the proposed approach, this thesis work doesn't address any comparative study on different statistical methods beyond VMEA. Also, it does not attempt to forecast the economic impact of implementing such a method within the organization. The attention is confined to improve the technical decisions making, design traceability and robustness during the preliminary engineering design stages.

1.5 Thesis Outline

The thesis is organized into six chapters to present the details of the studies. From literature reviews, theoretical methods, qualitative research, computational results, and conclusions are covered in these chapters.

Chapter 1: Introduction

This chapter introduces the domain area of research and discusses the basics in relevance to design margins, uncertainty in design parameters, and the industry perspectives on deterministic design methods and possibly its improvement with probabilistic approaches. Also, introduction to GKN Aerospace, particularly its structural design aspects and future vision are briefly described.

Chapter 2: Theoretical Background

Chapter 2 presents the theoretical background, introducing different probabilistic approaches such as Design of Experiments (DOE), Design for Six Sigma (DFSS), Failure Mode and Effect Analysis (FMEA), Variation Mode and Effect Analysis (VMEA). Here, Affinity and Interrelationship Method (AIM) is explained, which is later employed in the qualitative study.

Chapter 3: Methodology

The third chapter establishes the methodological framework that sets the required procedures and steps to carry out both qualitative and quantitative research works on robust design, regards to structural components of aero-engine. Main emphasis is placed on describing the procedures for the robustness and sensitivity analysis, and reliability. It further outlines the steps taken to ensure validity and transparency, strengthening the importance of the set research activities.

Chapter 4: Interview Study

Chapter 4 is devoted entirely to cover the qualitative aspect of the conducted research study at GKN Aerospace. It gives the details on the designed interview framework, structure, and execution process. Furthermore, comprehensive methods of data analysis, including the execution and interpretation of results from the Affinity and Interrelationship Method (AIM) workshop are presented. This chapter also synthesizes the insights and perceptions of industry experts on prevalent industrial challenges, gaps, and potential opportunities, in relation to the management and implementation of design margins, robustness, and uncertainties within aerospace engineering.

Chapter 5: Computational Study

The fifth chapter provides the conducted quantitative and computational analyses through detailed case studies, utilizing OptiSLang and the VMEA framework. The major focus is laid on to perform the probabilistic analyses of selected components such as the steel hook and mounted lug. Subsequently, the results are presented to show the application and benefits of using probabilistic design approaches along with the traditional deterministic methods.

Chapter 6: Conclusion

It provides a critical evaluation of the research methodologies employed, explicitly addressing and answering the formulated research questions, and summarizing the key findings in a structured manner. This chapter also gives the broader implications of the research outcomes within GKN Aerospace and other aerospace industries at large. Finally, it presents insightful recommendations to support the ongoing process improvements, identifies areas for potential future research, and highlights the contribution of this study towards robust aerospace structural design practices.

2

Theoretical Background

In this chapter, a broad overview of various methods and concepts is presented to establish the theoretical background for the present study. Further, the terminologies associated with the work have been carefully described in separate sections. A comprehensive picture of the methodology is presented in Figure 2.1, showing all the key approaches/elements to display their interconnectivity, in order to carry out the set aims and objectives in chapter 1.

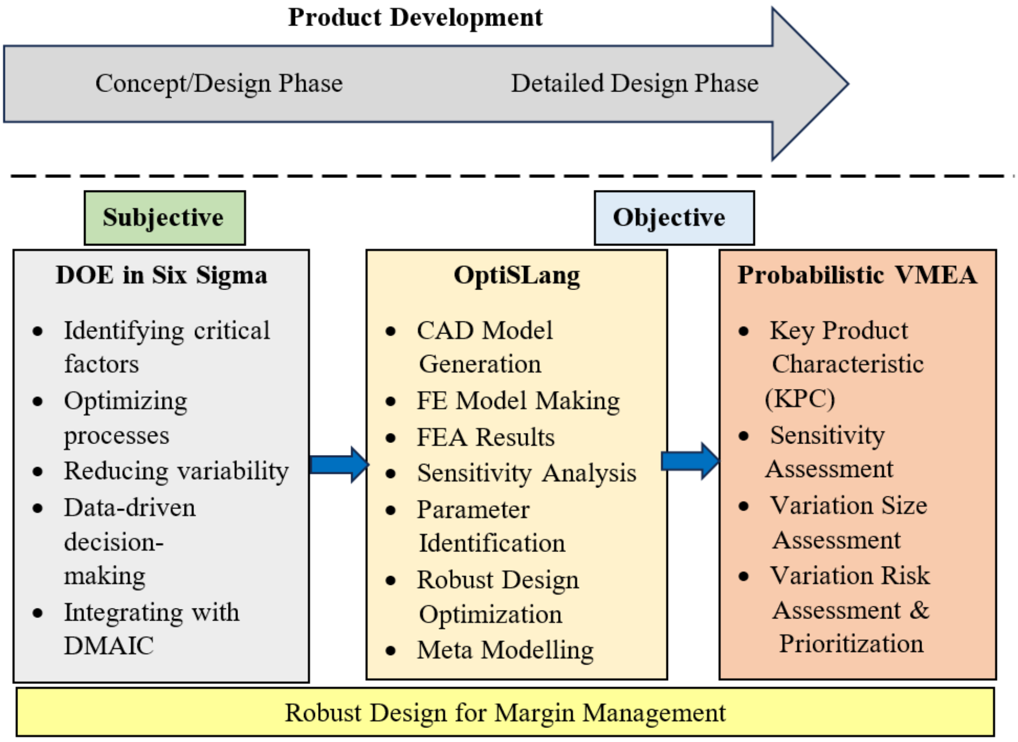


Figure 2.1: Schematic of important stages in Robust Design Methodology

Robust Design Methodology (RDM) is a promising non-traditional approach and its application is fast emerging in different engineering fields [[3, 4, 5, 6]]. It strategically integrates the probabilistic VMEA with deterministic design philosophy within the DFSS quality framework, so that the significance of RDM is appreciated in the context of aerospace structural design and its relevance to design margins. Further, the important literatures are thoroughly reviewed in the considered problem domain, such that the various engineering aspects like robust design, DFSS, DOE, uncertainty, design margin, FMEA and VMEA are meaningfully tracked.

2.1 Robust Design

Robust design is an advanced concept that can equip the modern engineering to make sure a consistent performance for the developed systems and components [[5, 6, 15]]. It considers the variations in processes, deviations in tolerances during manufacturing, and various uncertainties arising out of operational environmental conditions. During the years 1950 to 1960, Taguchi method was developed in Japan, which is a powerful technique for optimizing the processes to enhance the product quality [[27]]. It was later (1987) introduced in other countries as a part of quality engineering to minimize the variation in the process [[28]]. In the recent years, robust design has progressed well as a development framework and its application is recommended to multiple fields of Engineering for assuring product reliability and performance [[5, 6]]. Aerospace sector always demands high performance and safety for all the components and systems, where robust design can find its prominent place [[29]]. To achieve robustness, the sensitivity to several noise factors i.e. variables, needs to be minimised as they are not controllable while operating the product, even without removing the source itself. Several researchers have studied this approach and reported that the components and systems can be produced to achieve the intended functional performances, in spite of uncontrollable variations [[10, 11, 12, 13, 30, 31, 32],].

The purpose of robust design is not only to get optimal configuration or performance in perfect conditions, but also to ensure the required operational performance under different real time uncertainties. This is achieved by optimizing the signal-to-noise (S/N) ratio. Here, the "signal" is the desired value and the "noise" denotes the variation that occurs due to external or internal uncertainties. The Taguchi's loss function captures any deviation from the target performance, which is associated with societal cost, bringing quality, customer satisfaction, and economic impact via robust design [[27]]. It is to be noted that the failure of any component or system in aerospace product, involves substantial cost and catastrophic risk. The relevant literature recognises the merits of robust design methodology and recommends this concept for achieving tolerance to variability in materials, geometry, and environmental conditions to overcome the conservative safety margins [[3, 5, 33]].

In general, the designers can use the robust design approach to quantify the trade-offs amid competing objectives, for example structural integrity versus weight reduction. This exactly aligns with the perspectives of many researchers, who have proposed the robust design as a tool to guide the decision-making under uncertainty [[5, 10, 15, 16]]. It is therefore evident that, by incorporating the robust design philosophy as guiding principle, the aerospace industry can improve its product quality, having lower life cycle cost, and accurate performance prediction. This is more suitable for a product development, where in new technologies are introduced, to be operated in conditions with unexpected variations that can critically affect the product performance. In summary, robust design has got many promising features that promote an efficient quality control philosophy for the design of components or systems to be reliable and high performing, across a wider range of operating conditions [[4]].

In the following subsections, we discuss two important concepts, namely design for six sigma (DFSS) and design of experiments (DOE), which are fundamental to robust design methodology (RDM). DFSS assures controllable variability in the component, considering the variability as a normal distribution, so that the potential extreme design points are eliminated to achieve a better reliability index. On the other hand, DOE is a structured approach, which helps to plan, conduct, and analyze the experiments systematically, and to investigate, how the input variables (factors) inflence the output variables (responses).

2.1.1 Design for Six Sigma (DFSS)

Design for Six Sigma (DFSS) is a quality related paradigm [[34]] and it is an organised data-driven approach. DMAIC (Define, Measure, Analyze, Improve, Control) is a traditional Six Sigma procedure that deals with process improvement. In contrast, DFSS is applied to the design of products and systems, where the customer needs are met through robustness in the product's specifications [[35]]. DMADV (Define, Measure, Analyze, Design, and Verify) is a very popular DFSS approach, which detects and evaluates the critical to quality (CTQ) parameters, very early in the product development stage to make sure the functional and engineering requirements [[36, 37]]. Quality Function Deployment (QFD), Failure Modes and Effects Analysis (FMEA), and Design of Experiments (DOE) are regularly practised within DFSS framework, to provide accountability for the design decisions in order to be quantifiable and traceable.

DFSS offers many advantages to aerospace engineering applications, where very expensive components, stringent compliances, and higher development cost and time are involved. This methodology can predict the risk and sources of variation at the earliest, so that design rework, numbers of testing, and stagnation in development are minimised. In the current work, DFSS is conceptually associated with the goals of VMEA methodology (to be discussed in Section 2.6), specifically to address early risk identification and mitigation point of views through a structural analysis scheme. The computational simulations also support DFSS principles by integrating DOE techniques and probabilistic models, to verify the design performance, considering multiple scenarios. For instance, the structural optimization is aligned with DFSS's "Design" and "Verify" phases, demonstrating the performance robustness across varying loads and geometries. The maturity in design is tangible, when statistical approach along with customer-based metrics are included in the initial design phases using DFSS [[37]].

Application of DFSS into the design of aerospace components can bring a lot of benefits like optimized for manufacturability, cost-effectiveness, compliance with regulatory standards, and in-service reliability. Therefore, it is strategically placeable that integration of DFSS in aerospace structural design and development methodology, makes the products, quality assured, operation capable, and certifiable for flightworthy.

2.1.2 Design of Experiments (DOE)

Design of Experiments (DOE) is a statistical approach, which forms the linkage to design factors with performance parameters [[38]]. DOE establishes the basis for robust design and DFSS concepts. DOE helps engineering optimization with a focus to determine the key variables and how to reduce variability and finally to predict the output performances in various conditions.

In DOE, the input factors are varied methodically and its impact on the outputs are observed [[18]]. Thus, the engineers can adopt strategies for factor interactions to critically select the design optimization parameters for creating predictive analytical models. It is interesting to note that DOE supports aerospace industry to achieve a lower weight policy, meeting the target design service goal (fatigue life), addressing the design trade-offs under uncertainty. The major benefits DOE offers are that minimizing the number of simulations and limited experiments based on its valid statistical inferences. Classical DOE approaches cover fractional factorials, full factorial designs, Taguchi methods, and response surface methodology (RSM). Obviously, each one has its merits, according to the set objectives and the experimental limitations.

2.1.3 Section Summary

RDM, involving DOE and DFSS is a useful approach to improve the structural design that is less sensitive to variations in input factors (noise). Further, this method can be adopted for the design optimization process to develop a reliable component or product that can perform resiliently with a consistent quality and performance across varying operating conditions.

2.2 Uncertainty

The lack of complete knowledge or confidence about the system's behaviour, its state or outcome, is known as uncertainty in the system [[6]]. It directly influences the product performance and its reliability. Aleatory is a kind of uncertainty that is coming out of inherent randomness, e.g., variations in material data. On the other hand, epistemic is another type, which is explicitly introduced, e.g., model assumptions and approximations or measurement errors etc. Nevertheless, both these uncertainties are found to be very relevant for aerospace designers to consider in order to meet the tight performance margins, avoiding any system failure [[11, 12, 13, 39]].

Due to uncertainty, the hidden parameters in a product can pose difficulty to achieve robustness and reliability. It is true that deterministic approaches consider fixed values as design inputs but practically the systems are subjected to many disturbances such as deviations in fabrication, discrepancies in materials, added to these, unpredictable operational variances. Neglecting such factors can lead to either over-design i.e. leading to cost and weight penalties or under-design i.e. compromising safety and performance. It is vital to incorporate uncertainty early in the design process for reducing the life cycle risk and simultaneously improves product adaptability [[16]].

The importance of mapping and classifying uncertainties are reported as primary design focus and priority by Eckert et al., [[13]]. It is evident from their findings that using uncertainty classifications, the design can manage variation in certain controllable variables and the others are to be absorbed in the design process itself. In fact, uncertainty has many implications that are beyond technical performance, e.g., project planning and allocation of resources, which bring pressure on certification timelines. It is also well known that the aerospace products should meet stringent norms, high performance standards, and maintain airworthiness during its service life [36-38]. It is therefore advantageous that uncertainty must be inclusive in the design and development process to mitigate the unknown problems, besides successfully reaching out to regulatory requirements. Thus, uncertainty management is both a technical necessity and a strategic enabler.

2.3 Design Margins

Design margins are traditionally practised in engineering calculations, while developing any physical component or system [[11]]. They account for the uncertainties in the computed loads, measured material data, machining tolerances, and various operating conditions, indirectly. Aerospace industries very strictly follow these margins during the design and development phases to show compliance for airworthiness, besides satisfying the reliability and safety [[7, 8, 9, 25, 26]]. Nevertheless, the designers are not always able to justify the adopted margin policy, which is sometimes excessive or poorly miscalculated, leading to increased weight penalty, higher operation cost, or even underperformance [[13]].

Margins are introduced in a product development process to meet many requirements, such as customer requirement, regulatory requirement, safety requirement, and market requirement [[40]]. However, structural design margins are focused on safety, operation performance, and reliability. Therefore, it is beneficial to apply margin rationalization policy in model-based engineering design, so that margins can be calibrated with respect to different data base, risk evaluation, associated sensitivity [[40]]. The margin policy must be structured, if not, the unstructured margin criteria will hide design transparency and traceability [[12, 13, 18]].

The aerospace industry has been continuously accepting advanced digital techniques to develop future high performance, multi-role flight vehicles [[41, 42]], where the margin policy and its management become very essential. Physics based modelling, past failure data record, and stochastic analytics are employed to arrive at a balance between performance and robustness. By combining the digital tools with sensitivity analysis, the designer's confidence level is increased to measure the contribution of each margin towards intended performance, facilitating informed trade-offs. Even though the design margins are the essential part of aerospace product development, they need systematic justification, data-supported calibration, and transparent integration to get validation in the overall design process. Such an approach not only upholds safety but also advances sustainability and performance goals.

2.4 Probabilistic Design

Probabilistic design is a methodology, involving statistical or stochastic procedures that accounts for the uncertainties in material characteristics, system parameters, and environmental conditions [[31, 29, 43]]. Deterministic design considers fixed input values; however probabilistic approaches accommodate the variability in actual systems, besides ensuring the needed performance under critical operating conditions. Probabilistic design is an attractive solution to aerospace domain, where its components are sensitive to variations and require fault-tolerant performance [[18, 19]]. It offers a rigorous outline for quantifying the parameters, namely likelihood of failure, reliability levels, and risk exposure. Tools are proposed to perform reliability-based design optimization (RBDO) and uncertainty quantification (UQ) as core enablers in design approach [[44, 45]].

Probabilistic design is a robust approach that performs design under uncertainty. It is done at three levels, namely uncertainty modelling, uncertainty analysis, and design under uncertainty [[46]]. Uncertainty modelling quantifies the variability in design inputs and represents the uncertain variables with probability distributions. Uncertainty analysis is performed to identify and quantify the propagating uncertainties in design inputs, so that a range of possible outcomes and their probabilities are calculated. This helps to evaluate the robustness in the design and its performance under varying working conditions. Design under uncertainty introduces the mitigation plan to minimize the impact of uncertainty by making appropriate design decisions, as per the design needs. It is an iterative process and therefore, design is continuously updated until it reaches the desired optimal configuration. Uncertainty analysis is done for each updated design.

2.4.1 Monte Carlo Simulation

Monte Carlo Simulation (MCS) is a popular probabilistic technique that computes the distribution of outcomes by performing a large number of random experiments [[47]]. It is mostly effective, when the input is non-linear in a complex design domain and also analytical solutions are not feasible to get the probable design outcomes. In such cases, MCS generates random samples from the probability distributions using uncertain input parameters, producing likelihood of outcomes in a broader sense for observation. In aerospace domain, MCS is widely adopted for fatigue life computation, thermal performance simulation, and structural reliability assessment. In comparison to simpler statistical methods, MCS provides a comprehensive picture of performance under uncertainty, assisting robust decision-making, for example OptiSLang has MCS as one of the reliability simulation techniques.

2.4.2 OptiSLang

OptiSLang is a simulation and optimization platform, developed by Dynardo (Ansys®), which facilitates sensitivity analysis, uncertainty quantification, and robust design optimization. It offers very advanced tools like meta-modelling, variance-based sensitivity indices, and space-filling design techniques. In the present thesis, the computational experiments will be extensively carried out in OptiSLang to implement Latin Hypercube Sampling, to assess robustness criteria, and identify key design variables. In fact, the design exploration and probabilistic modelling in this software platform can provide a pathway to systematically evaluate uncertainty propagation and visualize the performance envelopes. Using OptiSLang, surrogate models will be developed, which significantly reduce the computational cost of running complex simulations. Subsequently, these surrogate models will be used to predict the performance across wide range of parameters, to conduct optimization that balances conflicting targets like weight and stress. Overall, the features in OptiSLang are found to be a powerful tool for modern probabilistic design, aligning seamlessly with the principles of robust design, DFSS, and VMEA, as discussed throughout in this chapter.

2.4.3 Section Summary

Probabilistic design permits the engineers to capture not only the performance of a component but also its variability. This shift in design approach allows the worst-case safety factors to go through statistical confidence-based criteria, to produce more efficient and meaningful results. OptiSLang provides one such probabilistic design domain, where in the robustness, reliability, and quality can be comprehensively addressed in the design process using VMEA method.

2.5 Failure Modes and Effects Analysis (FMEA)

Failure Modes and Effects Analysis (FMEA) is a structured, qualitative approach [[48]]. It is used in different fields to identify possible failure modes in a system, measure the associated risks, and prioritize mitigation efforts. FMEA is a popular risk assessment tool during product development phase, that captures known and anticipated design and process vulnerabilities [[49]]. FMEA is originated from aerospace and military systems that highlights its importance in safety-critical environments, where failures eventually produce catastrophic consequences [[50]]. The structure of FMEA consists of finding the failure modes, determining their effects and causes, and detectability. A numerical score is assigned for each envisaged failure based on three criteria: Severity (S), Occurrence (O), and Detection (D). Further, combining these scores, the Risk Priority Number (RPN = S $\times$ O $\times$ D) is estimated, which engineers will use to rank and address the most critical risks.

Moreover, application of FMEA also reveals its limitations in modern aerospace contexts. Specifically, its deterministic nature and heavy reliance on subjective scoring makes it less capable of addressing uncertainty and variation in input parameters. It is to be noted that the traditional FMEA is unable to solve the high-variations in complex systems, especially the ones susceptible to probabilistic phenomena. Also, FMEA may miss to predict some critical failure patterns because it does not consider distributional effect, input correlation and magnitude of variation. Further, the static treatment of parameters by FMEA limits its ability to examine the evolving risks over longer time, specifically under cyclic loading, environmental degradation or thermal fatigue [[11, 12]].

2.6 Variation Mode and Effect Analysis (VMEA)

Variation Mode and Effect Analysis (VMEA) is an advanced version of FMEA concept, which accounts for the uncertainty, variability, and interaction effects in a novel way within probabilistic domain, collaborating with standard design tools like CAD and CAE [[4]]. VMEA has overcome the shortcomings of FMEA in variation-sensitive applications, requiring high-precision. Figure 2.2 pictorially explains the different variants of VMEA.

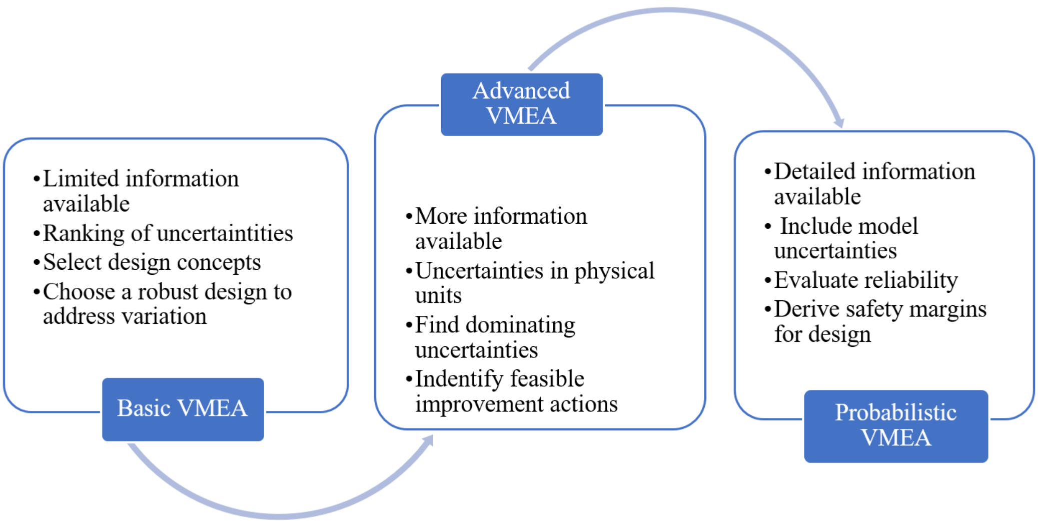


Figure 2.2: Different Varients of VMEA

It employs statistical analysis, simulation data, and design of experiments to quantify the variation in design inputs to assess their effects on system performance [[18]]. Figure 2.3 shows a typical VMEA application in the design and improvement cycle.

VMEA provides easy handling of variation through traceable and transparent documentation. Such practices are essential for aerospace industry, where risk identification and mitigation plan are the part of compliance requirement [[13]]. Failure-Variation Mode and Effect Analysis (F-VMEA) is another method developed, which not only find and assess the unwanted variations in the product, but also the envisaged degradations and failure of its internal elements [[51]]. In relevance to present study, the compatibility of VMEA with OptiSLang has facilitated the probabilistic design, robust optimization, and uncertainty quantification workflows. Further, using this platform, the robustness evaluation in digital simulation framework is addressed.

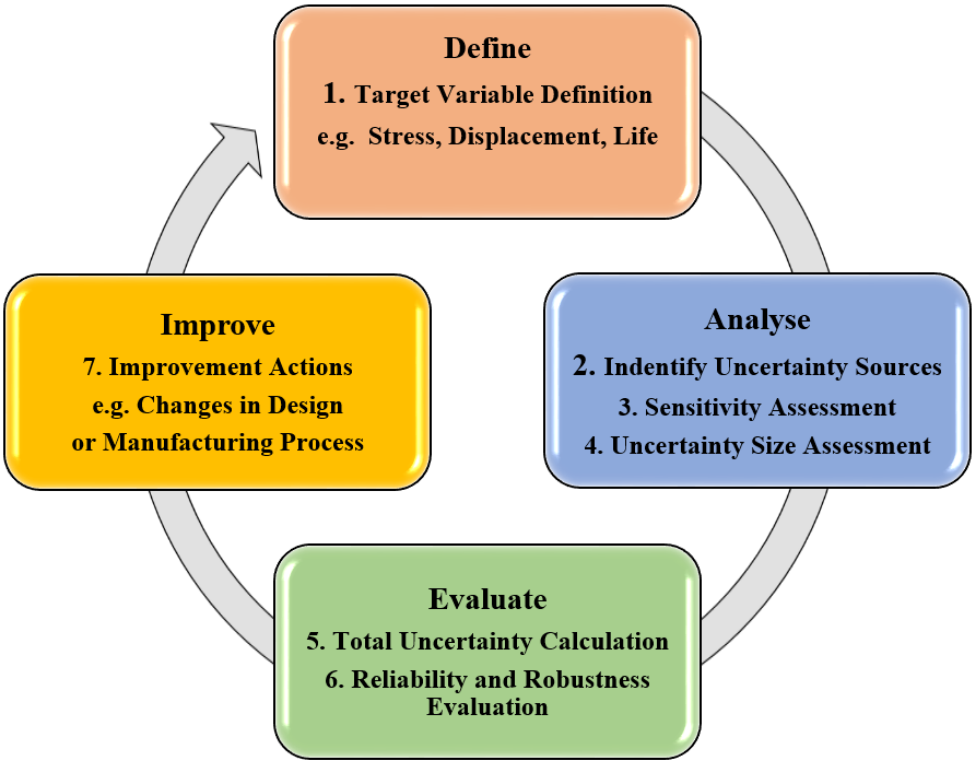


Figure 2.3: Application of VMEA in the Design and Improvement Cycle

2.7 Comparative Study: FMEA versus VMEA)

Figure 2.4 provides a table of comparisons between these two methods, which the engineering industries are either practising or looking forward to adopt for their product development process. FMEA (bottom-up approach) and VMEA (top-down approach), represent basically two distinctive paradigms, employing statistical and probabilistic frameworks, respectively to resolve design risk assessment. FMEA is scenario-based and qualitative, whereas VMEA is variability-focused and quantitative. This shift is critical in high-reliability industries, where optimizing the margin, reducing the weight, and predicting the performance, are considered as core design goals.

FMEA is an analytical deterministic method, which is practised by industries as a preventive quality management tool in product and process development. It is primarily focussed on potential failures and their impact on product performance. In contrast, VMEA is a probabilistic method that considers the variations of input parameters into the design process and study their impact on product performance, reliability, and robustness.

Aspect	FMEA	VMEA
Nature of Analysis	Deterministic; categorical failure modes	Statistical; continuous variation modelling
Output Focus	Discrete failures and effects	Performance sensitivity and propagation of variation
Data Basis	Expert judgment and historical failure data	Simulation, DOE, probabilistic distributions
Quantification Metric	Risk Priority Number (RPN)	Sensitivity indices, variation impact scores
Tools Used	Checklists, scoring matrices	DOE, Monte Carlo, OptiSLang, surrogate models
Limitation	Subjectivity, limited interaction modelling	Computational intensity, requires advanced statistical capability
Use Case	Early design reviews, compliance checklists	Robustness analysis, margin justification, probabilistic design

Figure 2.4: Table of comparision between FMEA and VMEA

FMEA does not require much information to evaluate risk or predict failure in advance and to propose suitable actions, whereas VMEA needs a very detailed information about the variations and their potential effects in the early design stage to arrive at right design decisions. FMEA generally takes into considerations activities such as manufacturing of various parts, assembly, and other process related events. But the scope of VMEA is broader, covering variations and uncertainty in design, manufacturing, and operational conditions. VMEA is best suitable for the design of complex systems, which require robust design methodology to improve quality and reliability for ensuring reduced risk of soft failures, compared to traditional FMEA method that is appropriate to identify possible failures. Nevertheless, VMEA is a computationally intensive approach, in comparison to FMEA that uses only simple analytical calculations.

In summary, FMEA offers a general knowledge of potential failures in a product during its development phase, while VMEA performs a very rigorous evaluations into how variations are related to those failures and to assess their impact on system performance and reliability. The current thesis seeks to address the limitations of existing robustness practices in the engineering workbench and propose a simulation-driven path forward, in which VMEA will serves as a basic tool, both conceptually and practically for navigating uncertainty to improve the design outcomes.

3

Methodology

3.1 Research study

The present thesis adopts a dual method strategy, combining qualitative inquiry with computational simulation to investigate the design margins and uncertainty within the engineering design process at GKN Aerospace. The study is therefore positioned within a practical engineering context, aiming not only to describe the current design practices, but also to assess the application of probabilistic VMEA method to improve the early phase design in terms of robustness and traceability. The decision to employ both interview-based review and design focused experimentation reflects the need to jointly address the process related and technical aspects of our research questions (refer to Chapter 1).

The research has been conducted in two parallel streams (refer to figure 3.1).

In the first, the qualitative assessment is carried out through interviews with engineers from different departments at GKN Aerospace. These conversations have been structured to understand that, how the design decisions are made in practice, particularly concerning the justification and application of design margins. This part of the study wants to explore, whether the uncertainty is formally evaluated during the early design stages or is it mainly addressed through generalized assumptions and safety buffers. By capturing engineers' views on existing methods, constraints and expectations, the qualitative study has laid the foundation for assessing the practical relevance and feasibility of using structured variation tools.

The second stream consists of a computational study that is focused on a fatigue sensitive lug bracket. This part is selected due to its relevance in structural load paths and its suitability for variation analysis. A DOE approach is used to generate controlled input variation for the parameters such as thickness, hole diameter and load direction. These parameters are selected based on design guidelines and prior consultation with engineers and method experts, who have been involved in mechanical design and simulation activities. The output from this experiment has informed that the influence of parameter variation can be visualized and the inputs are assessed by a simplified VMEA. As a result, the design parameters that have strongest impact on performance metrics, namely maximum stress and deformation, are diagnosed based on their sensitivity.

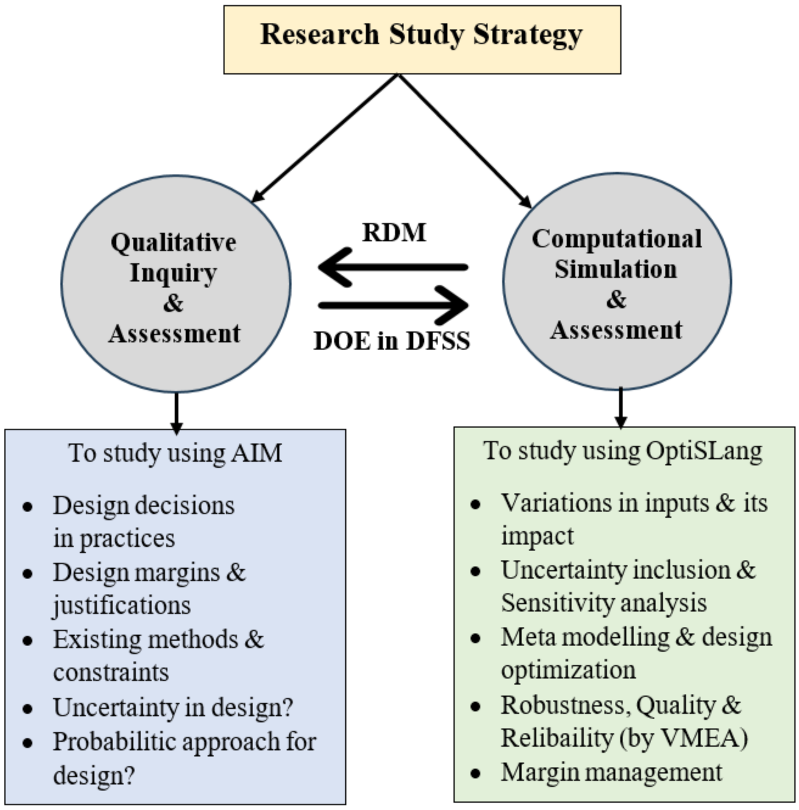


Figure 3.1: Concept diagram for the current research study

Instead of treating the qualitative and computational study as two separate efforts, the present study is designed to allow one to inform the other for mutual interaction. Interviews have helped to recognise those areas, where the engineers have felt that uncertainty is neglected or poorly documented. Further, the case study has provided evidences that, how hidden uncertainty can be captured using probabilistic method. This integrated approach has allowed the research to engage with the problem from both behavioural and technical perspectives, providing the depth and contextual validity to the findings.

This methodological approach aligns with a pragmatist research paradigm, which emphasizes on risk minded approach of thinking, outcomes, application, and context specific utility. The intent is to develop a universal framework but to determine whether probabilistic approach like VMEA can realistically support decision making in a specific organizational environment. In doing so, the study prioritizes the practical feasibility and integration potential over theoretical generalization.

Data from the qualitative study are coded thematically with an attention given to robust design; in particular, how the design margins are introduced; how uncertainty is perceived across various functional departments; and whether engineers envisage the value what the probabilistic tools may offer. The results are not intended to produce statistical generalizations but rather to surface the underlying patterns and decision habits, such that the design robustness is shape as desired. These insights are then carefully considered, when interpreting the outcome of the computational study, to evaluate the value addition of VMEA to the existing design process.

The decision to combine the qualitative feedback with a simplified case study has been driven by the nature of our two research questions as well as the industrial relevance of the problem. The challenges associated with documenting and justifying margins are not purely technical but they also involve organizational behaviours, tool familiarity and the constraints of time and resources. Therefore, the research plan reflects a need to understand the engineering design process not only in terms of inputs and outputs but also as a dynamic environment, to be shaped by both formal procedures and implicit knowledge.

3.2 Qualitative Study

The qualitative study of this thesis has focused on understanding that, how engineers at GKN Aerospace currently perceive and manage uncertainty, design margins, and robustness during early stages of development. It is structured around a set of semi-structured interviews, conducted with eleven engineers from a range of departments, spanning both commercial and space divisions. The aim is to gather insights into real world practices, attitudes and limitations that are associated with deterministic design and to explore the extent to which the probabilistic approaches are known, accepted or already used.

The interviews have been designed to explore the following five key themes:

1.Understanding robust design

2.Awareness and use of Design margins

3.Handling of uncertainty in their field of work

4.Familiarity with probabilistic methods like Monte Carlo or VMEA

5.Perceived challenges and opportunities if such method were to be applied in future.

The questions have been open ended, allowing the interviewees to elaborate on their specific experiences; at the same time enabling the interviewers to follow up on relevant tangents or unique cases. This flexibility has provided a deeper insight into how engineers view the current processes and what they see as potential areas for improvement.

The choice of participants from GKN Aerospace was made to ensure a balanced representation of roles and experience levels. The interviewees are represented by the design engineers, stress analysts, team leads and method experts from various functional departments. Their varying perspectives have helped to uncover, not only the technical gaps but also the organizational and cultural factors that may impact the robustness in design practice. Interview responses are recorded according to the themes of robust design, uncertainty and design margin, in order to conduct an AIM workshop to classify the challenges specified by our interviewees.

3.3 Interviews at GKN Aerospace

As part of the Qualitative study of this thesis work interviews were conducted at GKN Aerospace to gain insight into how engineers interpret and manage design margins, robustness, and uncertainty within the early stages of product development. These conversations aimed to uncover not only the practical habits behind technical decisions but also the organizational mindset that governs how variation and reliability are addressed in real world design environments.

A total of 11 interviews were conducting involving engineers from different functions and project domains ranging from structural design and simulation to fatigue assessment and system integration. This broad spectrum was intentionally selected to ensure that the study captured a wide range of perspective from both commercial and space programs. The intention was to gather views that reflect real operational diversity rather than focusing solely on one product or process line.

No.	Department	Business Unit
1	Material AM GTC	GKN
2	Design GTC	GKN
3	Design GTC	GKN
4	Design GTC	GKN
5	Design Space Turbine (experienced)	GKN
6	AM & Quality	GKN
7	GTC	GKN
8	GTC	GKN
9	Mechanical Systems	GKN
10	Method Specialist	GKN
11	CDE Certification Engineer	GKN

Figure 3.2: Interviewee Background Table

The interviews were semi structured and guided by a set of core exploratory topics, which allowed for consistency across sessions, while giving participants the space to reflect freely on their own practices. Before each session, participants were briefed on the topic and the thesis goals and the purpose of conducting the interviews. All conversations were held confidentially and anonymized for internal reporting and thesis use. Most interviews lasted between 30 to 45 minutes either conducted in person or via online through Microsoft Teams depending on their availability.

During these sessions', engineers discussed how they interpret robustness in their respective design roles, how and when margins are typically applied, and how uncertainty is accounted for, if at all within their analysis or modelling efforts. A recurring theme across departments was the reliance on past experience and organizational norms, when applying safety buffer. While this practice often leads to conservative design outcomes, it also revealed a lack of structured traceability.

In addition to margin practices, the interviews touched on participants familiarity with probabilistic design tools. Very few engineers reported using such tools during the conceptual or preliminary design phases. Nevertheless, there was an openness to integrate more accessible forms of variation analysis particularly, if they could help visualize parameter influence or assist in documenting, why specific design choices were made.

3.3.1 Interview Framework of Questions

The development of the interview framework was established to directly address the research question (RQ1), while keeping the conversation accessible and relevant to engineers with diverse roles. Rather than relying on an off the shelf questionnaire or theory-based model, the framework was built around the real-world context of the current industrial challenges in the design environment (GKN Aerospace) and identify the recurring issues during the initial phases of the thesis.

The framework was reviewed internally with our external supervisor before interviews began to ensure that the phrasing of the questions was clear, non-leading, unbiased and tailored to participants, who might not be familiar with academic terminology. This also helped to confirm that the intended themes were both practical and relevant across different departments, ensuring that no group would be excluded due to unfamiliarity with specialized vocabulary and tools.

Each interview began with a few general background questions about the engineer's role, how long they had worked at GKN and their typical involvement in design and simulation tasks. These introductory questions helped to establish rapport, while providing useful context for interpreting their responses later on. From there, the framework gradually shifted more toward questions, starting with how robustness is understood and applied within their projects.

Rather than listing themes explicitly during interviews, we carefully phrased the questions to explore topics such as design rationale, assumptions and decision documentation. For example, to examine the use of margins engineers were asked, "When introducing a margin or tolerance in your design what factors guide that decision?". This allowed the respondents to share their personal reasoning, while offering challenged or justified through formal analysis.

To understand how uncertainty is approached, engineers were asked to describe, how they account for variability in geometry, loads or boundary conditions in the early stages of design. Questions were presented, for example, "Do you ever find yourself making assumptions that later prove critical?" or "What happens when input changes midway in the project?". This allowed the conversation to remain practical, while still surfacing the intended insights.

For those unfamiliar with probabilistic methods, a brief neutral description of the

VMEA method was provided, followed by a prompt such as “Would a method like this aid you in making early design decisions with more confidence or traceability?”. This helped gauge not only technical familiarity but also the perceived feasibility and usefulness of structured variation methods.

The final portion of the interview was designed to capture attitudes toward integration and change. Engineers were asked, what factors would motivate them to use a new method, what challenges they might anticipate, and how such tools could be introduced without disrupting their current workflow. Questions were framed to be straight forward and solution oriented, giving participants a chance to contribute ideas rather than simply critique current processes. Responses from this part of the interview helped to shape the final discussion of implementation potential within the thesis.

Importantly the framework was applied flexibly, while the same themes and core prompts were used across interviews. The order and emphasis varied depending on the flow of each conversation. In some cases, engineers naturally brought up issues of traceability or variation management before even we reached those topics. In such instances, we allowed the discussion to follow its natural course and only revisited the theme later to ensure completeness.

In summary, this adaptable yet focused framework allowed the research to extract consistent, high quality data from a diverse group of engineers across different functional teams and programs, while keeping each conversation authentic and reasonable. This supported the thesis objective of uncovering not only the current industrial challenges with regards to design margins and uncertainty, but also what is missing and how probabilistic methods like VMEA might realistically fill that gap in the future design workflows.

The AIM (Awareness, Implementation, and Maturity) diagram was presented as an interpretative lens in order to conduct a systematic analysis of the interview data that was gathered. The engineers understanding of robustness related ideas, the degree to which they had applied these methods in their work, and the maturity of these practices within their department or project setting were all taken into consideration when classifying their responses using this framework. The AIM diagram made it possible to identify trends, discrepancies, and areas for improvement by mapping information across these three dimensions. This method helped assess where and how structured variation techniques like VMEA could be practically included into early stage development workflows while also promoting a more nuanced knowledge of how design margins and uncertainty are currently managed in practice.

3.4 Quantitative Study

The research question RQ2 is answered through a computational study on achieving the robustness optimization of a model. The tool used for the exploration is OptiSLang, which is integrated into the workbench of ANSYS Mechanical Workbench 2021 R1. The tutorial provided by the developers of the tool is considered the base reference for the workflow, and further explorations are conducted with a few fundamental assumptions noted below.

3.4.1 Scope and assumptions

1. In the thesis, the discussion about the robustness of the design is only valued in the linear region of the stress-strain curve. Any design point that bears a response value beyond the yield limit is considered an undesirable design value and non-robust by default. Due to these important factors, only the linear material properties are considered for the computational study. A deterministic optimization is done followed by a robustness evaluation and reliability analysis. Final reliability verification is not conducted due to time and resource constraints.

2. In the thesis, there is an inherent assumption that the initial static analysis setup contains realistic boundary conditions and robustness could be achieved within a reasonable deviation from the nominal values. Even though, as a tool, OptiSlang is capable of handling extreme values, the scope of the investigation is limited to robustness optimization with the assumption that a realistic semi-optimized geometry is considered as the nominal geometry. It should also be noted that robustness optimization only adjusts the parameter values to achieve robustness in accordance with the user-defined criteria and doesn't conduct topology optimization. In a real-world industrial setup, it would be practically sound to conduct robustness optimization on a topology-optimized model, hence providing more validity to this assumption.

3. The design space or the range over which the parameters under consideration are allowed to vary is determined by various factors like customer demand, engineering factors such as dimensional and functional constraints of packing efficiency, performance in the context of the supersystem in which the design is embedded, manufacturing capabilities and demands. Within the thesis, there is an inherent assumption that robustness could be achieved within the design space specified and the thesis doesn't investigate the reasoning and criteria behind the development of the design space. The design space considered in the thesis is within a 10 percent deviation from the mean value of the parameters and stricter design values are imposed at the boundary conditions since those are the regions that interact with the other parts within the system. If it is found that robustness is not achievable within the above-specified design space, the design space is expanded to a reasonable limit determined by the minimum geometric requirements to keep the sketch closed to obtain an uncorrupted model. This modification is also subject to engineering judgment.

4. The nominal value of the parameter is considered as the mean value, which is allowed to vary as a normal distribution with a spread of 6 sigma within the specified design space.

5. The concept of robustness can be considered from different perspectives of causes of failure such as fatigue, creep, sudden impact, aerodynamic loads, and other thermo-mechanical loads. The scope of the computational study is limited to studying robustness optimization in terms of the maximum equivalent stress developed due to the application of external loads. Since the primary focus of the thesis is the exploration of a better workflow for handling robustness and not on solving existing mechanical challenges in design, this assumption holds validity. It should be noted that within the scope of the thesis, robustness optimization aims to minimize mass with respect to maximum stress, load, and other user-defined criteria, but does not aim to reduce overall stress.

6. The primary aim of the computational study is to exhibit the current workflow with the OptiSLang module in ANSYS mechanical Workbench compare the results and report observations with a proposed modified workflow. The modified workflow consists of a streamlined version of the current workflow integrated with the proposed method of probabilistic VMEA. The updated workflow is hypothesized to have benefits in computational time by arriving at the best robust design point in fewer steps.

3.4.2 Ansys OptiSLang workflow

The ANSYS mechanical workbench is an advanced tool that provides flexibility in the sequences of analyses that can be performed. The sequence followed in the initial part which is considered as the existing workflow in the thesis, adheres to the same sequence recommended by the developers of the workbench. To exemplify the workflow, a static structural analysis of a steel hook is considered, and the results of this analysis will be explained in the results section of the thesis.

3.4.2.1 Initial setup

The initial setup of static structural stress analysis is considered as the input for the OptiSLang robustness optimization. Parameters such as geometrical dimensions, material properties, and load uncertainties are considered variables that are varied in the robustness optimization. The geometric mass, equivalent stress and user-specified geometric constraints are considered as the responses. The best design is determined according to the values of the responses on which the constraints are imposed.

3.4.2.2 Robustness evaluation of the initial design

The goal of this initial robustness analysis is to understand the current state of robustness of the nominal design. The current status is evaluated by how the initial design performs under stochastic/probabilistic variations by iterating over a default sampling option of Advanced Latin Hypercube Sampling (ALHS) with 100 samples. The design space of 10 percent deviation to both sides of the mean is assigned by default and a normal distribution with a 6 sigma standard deviation is considered within the limits of the design space for each geometric and load parameter. All the geometric parameters are stochastically varied with the aim of optimization while the material and load uncertainties are only considered as stochastic without any intent for optimization.

The mean values is set to the nominal parameters values.

$$\mathrm{STD} = \frac{\text{Upper limit of range} - \text{lower limit of range}}{6}$$

$$\mathrm{CoV} = \frac{\mathrm{STD}}{\text{mean}}$$

Note that no criteria are defined in this robustness check and the robustness sampling algorithm employed is the recommended algorithm determined by the workbench according to OptiSlang's internal black box algorithm. A histogram plot is used to understand the current spread of the responses under the specified conditions. The plot is examined against the user-defined limit criteria to determine the probability of failure. This analysis also provides a plethora of information about the initial design, but within the scope of the investigation, the histogram is the main plot used in the thesis. Along with the failure probability, the values of the coefficient of variation (COV) and sigma level are also observed from the histogram. Depending on how the initial design performs under the stochastic changes, a case for further optimization is established. Figure 3.3 illustrates the general overview of the steps in robustness optimization.

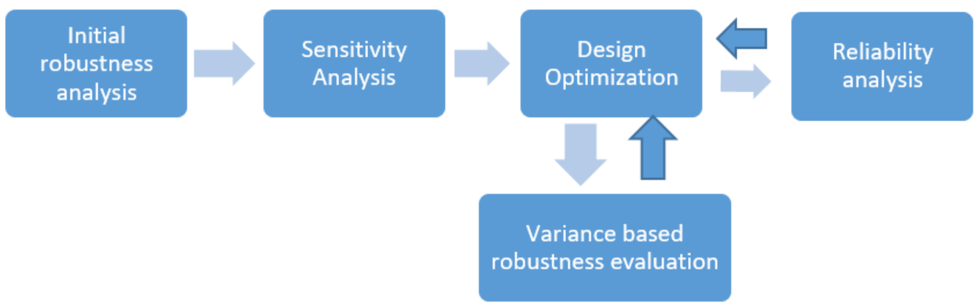


Figure 3.3: General workflow

3.4.2.3 First robust design optimization criteria

From the figure 3.4 [52], the requirements of 4.5 sigma difference from the limit of 300MPa can be formulated as,

$$\text{Mean stress} + 4.5 \times \text{Mean stress} \times \mathrm{CoV} \leq 300$$

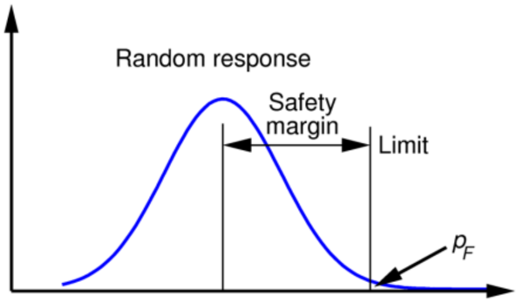


Figure 3.4: Limit diagram

$$\text{Mean stress} \leq 180$$

The obtained value of mean stress is employed to establish the stress criteria for the optimization cycle. Even though the yield stress of structural steel is 250 MPa, 300 MPa is defined as the limiting stress by the user. This can be interpreted as a pragmatic value to avoid over-constraining the design space. Even though the material plastically deforms at 300 MPa, it would not drastically fail at a slightly higher value than its yield strength. In realistic settings, variations in the yield point can also be expected. Hence, in the interest of avoiding an overly conservative design point, the selection of 300 MPa as the limit for the material of structural steel can be justified.

Note: The CoV value is taken from the robustness analysis histogram

3.4.2.4 Sensitivity Analysis

Criteria

Name	Type	Expression	Criterion	Limit	Evaluated expression
constr_Equivalent_Stress_Maximum	Constraint	Equivalent_Stress_Maximum	≤	180	270.261 ≤ 180
obj_Geometry_Mass	Objective	Geometry_Mass	MIN		1.09976
constr_Opening_Width	Constraint	Opening_Width	≥	50	64.3124 ≥ 50
new					

Figure 3.5: Criteria on the responses

The sensitivity analysis attempts to establish a surrogate model of the responses, also referred to as the Metamodel of Optimal Prognosis (MOP), through the machine learning approach of curve fitting. This MOP simulates the approximate behavior of the response [53]. The quality of the MOP is judged on the basis of a model-independent measure called the Coefficient of Prognosis (COP) [54]. Through OptiSLang's machine learning black box processes, sensitivity analysis quantifies which input parameters strongly influence the output responses based on the criteria in Figure 3.5. This identification of important parameters helps to strategize which parameters should be prioritized during the optimization stage. The parameters that have minimum to no impact on the responses are kept at the extreme values of the design space in accordance with the requirement. In this case, this practice reduces the dimensionality in certain regions that have no contribution toward the maximum stress and helps in mass reduction without impacting functionality. This analysis also gives insights into conflicting demands within the responses and the trade-offs of the optimal design.

The sensitivity module conducts a design of experiments and the sampling algorithm is kept as the default option recommended by the workbench. A sampling size of 300 is maintained as it is the default recommended value. The best design for the optimization is also selected from the sampling done in the sensitivity analysis.

3.4.2.5 Design Optimization

The parameters along with the best design from the sensitivity analysis are inherited by the optimization module. It is also feasible to manually select the design around which the optimization is conducted based on the judgment of the engineer. Additionally, in the optimization setup, the parameters that do not affect the responses are kept at their minimum values and treated as constants. The optimization is conducted within the design space region of the modified parameters based on the inherited design from the sensitivity analysis. The stochastic sampling is performed with a default sample size of 200 (which is the default recommenced sample size). This step yields an optimal design within several iterations, fulfilling all the constraint conditions. The optimized parameter values and the corresponding values of the responses are obtained as the final result of this stage.

3.4.2.6 Robustness analysis

The optimal design is checked for robustness based on the criteria and parameter range inherited from the optimization module. This step is similar to the initial robustness evaluation in the earlier stage and the current state of robustness is obtained from the distribution observed in the histogram. The optimization is likely to yield a better sigma value with a lower probability of failure. These values must be further verified through a reliability analysis.

The sigma value obtained is based on the assumption that the response (the maximum stress value) is spread over a normal distribution with a constant single value for the limiting criteria. Realistically, variation in the limiting value of 300 MPa should be expected. Hence, to ensure that the robustness value obtained is sufficient under the predefined criteria, further investigation is conducted.

3.4.2.7 Reliability analysis

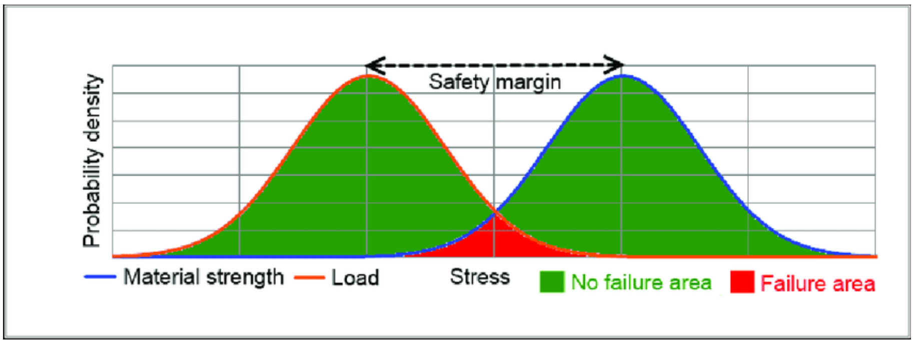


Figure 3.6: Reliability analysis

Further verification of the robustness is achieved through the reliability analysis. All non-contributing geometric, load parameters and material properties are kept constant to simplify the computation. The failure limit is defined as per the original initial requirement from the user and the limit is also considered as a distribution using the uncertainty knowledge option in the robustness wizard. The new situation is illustrated in Figure 3.6. In this wizard, the desired sigma level is also specified.

The analysis samples over 300 different design variations and calculates the probability of failure from which the sigma level can be interfered from the probability of failure and the reliability number is obtained. The entire generic OptiSLang workflow process is illustrated in Figure 3.7.

If the probability of failure obtained is higher than the desired sigma level, then the same cycle of optimization with stricter criteria is executed. The new criteria value can be extrapolated from a linear consideration of the reliability index and the mean stress from the previous optimization cycle.

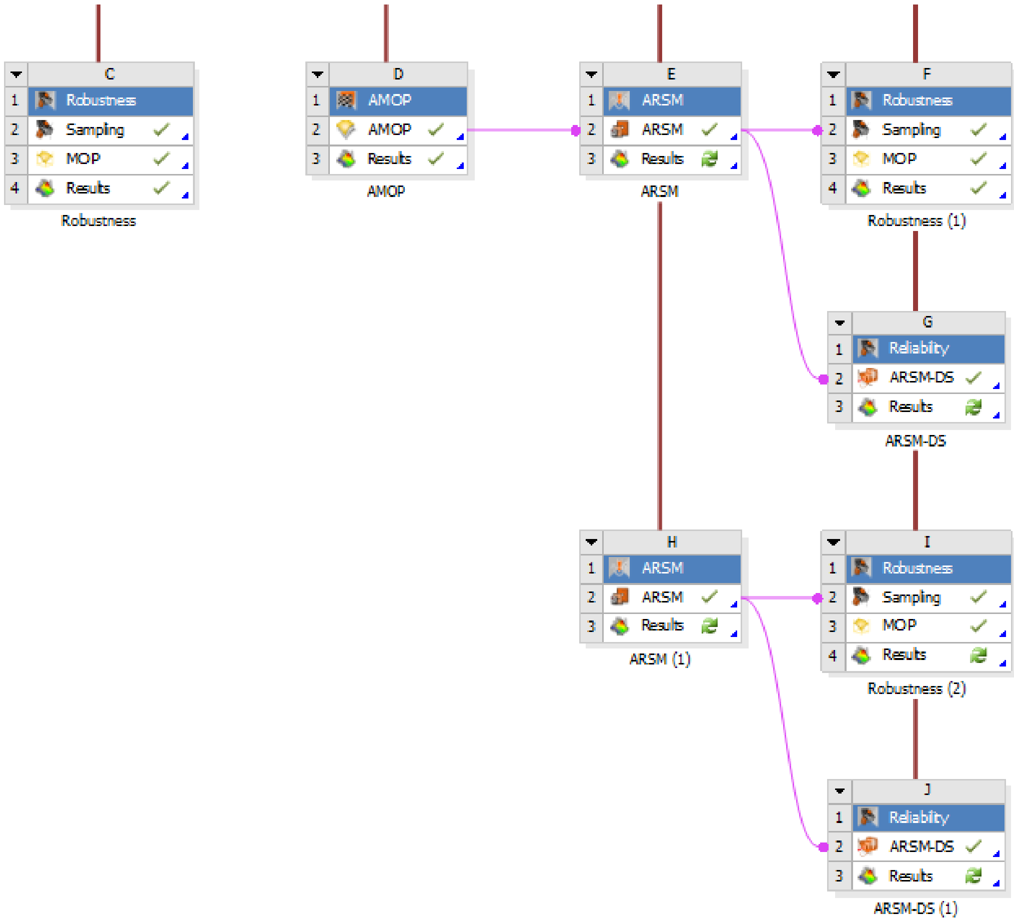


Figure 3.7: General OptiSLang workflow

3.4.3 Probabilistic VMEA integrated OptiSLang workflow

The probabilistic VMEA integrated workflow also uses ANSYS OptiSLang and the results from the sensitivity analysis. The difference arises in the method of derivation of the criteria.

The parameters observed to have a stronger influence on the response, which is identified in the sensitivity analysis, are varied between their maximum and minimum values within a more constrained design space. The initial design space was assumed to follow a normal distribution and in order to capture realistic variation in the max-min a full factorial DOE is conducted in OptiSLang within a restricted new design space. A restriction of 1 sigma level from the extreme limits of the range is imposed on the initial design space as shown in Table 3.1. The average values of the range of noncontributing parameters are also considered for the full factorial DOE.

Ranges and average values of parameters					
Parameter	Type	Min	Average	Max	Unit
A	Outer_Diameter	28	31,5	35	mm
B	Connection_Length	20	35	50	mm
C	Connection_Angle	120	135	150	degree
D	Upper_Blend_Radius	18	20	22	mm
E	lower_blend_radius	18	20	22	mm
F	Opening_Angle	10	20	30	degree
G	LowerRadius	47		53	mm
H	Fillet_Radius	2,4		3,6	mm
I	Thickness	17		23	mm
J	Depth	17		23	mm
K	Density		7850		
L	Youngs modulus	1,90E+11		2,10E+11	
M	Poisson	0,285		0,315	
N	Force Y	-5400		-6600	

Table 3.1: Design space for Probabilistic VMEA

The average values of the responses for the new parameter ranges and the total average value are calculated from the full factorial DOE. These values are converted to log scale and the differences in the log values for each parameter are divided by 6, and the root square sum (RSS) of all the considered parameters is calculated. The RSS is then multiplied by the user-defined sigma value (4.5 sigma in this thesis) and subtracted from the total average value. The result is converted back to a linear scale. This value of the response (maximum stress) obtained through the probabilistic VMEA method is used as the criteria for optimization. The design point selected through the VMEA criteria is hypothesized to result in the best optimal design without requiring iterative optimization cycles.

It must be noted that the results from the initial sensitivity analysis are used to prioritize the parameters in the full factorial DOE. The module referred to as VMEA is the same as the initial sensitivity analysis and is conducted separately only to illustrate the sequence in the integrated workflow in Figure 3.8.

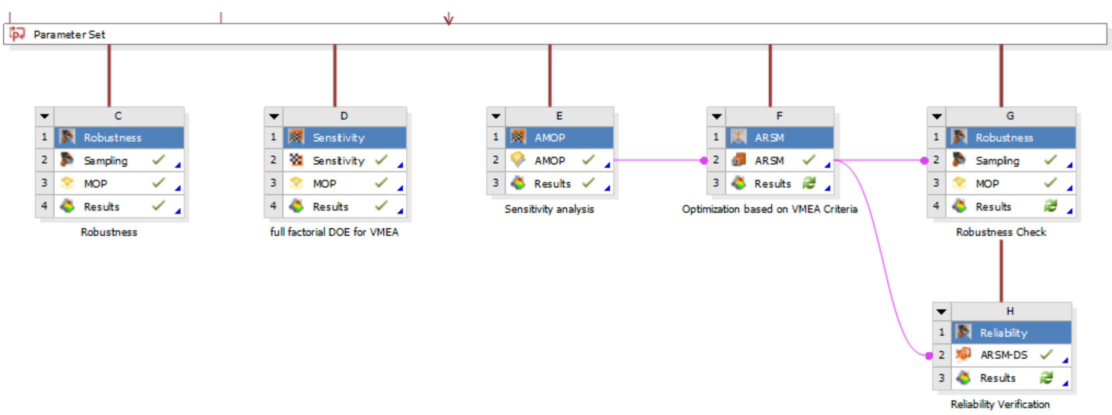


Figure 3.8: OptiSLang workflow using probabilistic VMEA

3.5 Conclusion

The methodological approach considered in the thesis was designed not only to extract data but also to provide clearer navigation through complexities and explore a possible solution in industrial design practices. Rather than forcing premature structure, the methods aimed to embrace uncertainty as a condition to be understood.

The use of semi-structured interviews allowed for open conversations that were informal enough to reveal patterns that were noted during the literature survey. These interviews were not just data points, but they were reflections of real engineering contexts, shaped by constraints, legacy processes, and human judgment.

Through the process of building the analysis around wide themes of robustness, uncertainty and design margins, the methodology created a lens that is wide enough and capable of capturing system-level challenges. The development of AIM diagrams gave structure to the emerging insights with clarity and an interpretive layer. The strength of the methodology lies in its capacity to listen and allow voices from backgrounds to be heard and through the process gather a broader understanding of the design process.

As the thesis progresses into quantitative investigations, the insights drawn from this methodological process will not simply be background context. They form the very foundation for proposing strategies and tools. Importantly, the methods adopted did not assume a perfectly rational design process. Instead, the messiness of real-world engineering where decisions are made under assumptions.

4

Qualitative study

4.1 Introduction

In this chapter, the results of the qualitative study conducted to address the research question RQ1 are discussed in detail. The analysis based on semi-structured interviews in the three interconnected themes of robust design, uncertainties and design margins resulted in unorganized data. To gain a structure and make sense of the wide range of insights generated, raw qualitative data was classified into themes and reasons through discussions, which translated into forming the foundation for constructing the AIM diagrams. This framework of AIM diagram is used as an analytical tool to organize qualitative data in a way that makes relationships between challenges more explicit.

In this organizing process, patterns began to emerge, and recurring concepts were grouped under subthemes. To preserve the traceability of findings and support clarity in navigating through multiple levels of abstraction, a consistent numbering convention was introduced. Each theme is prefixed by a letter R for robust design, U for uncertainty and D for design margin followed by numerals indicating subthemes and sub subthemes. This structured labeling also reflects the layered nature of industrial reasoning around these topics.

The order in which the AIM diagrams are discussed mirrors the sequence of themes discussed in the interview. This sequence is further supported by the logical relationship between the themes. Discussions around robust design often serve as the starting point, as organizations first articulate their goals in terms of reliability and performance. This naturally leads into the domain of uncertainty where the factors and unknowns that challenge the achievement of those goals are discussed. Design margins then emerge as one of the approaches through which companies respond to those uncertainties. In the sections that follow, each AIM diagram is introduced alongside detailed interpretations of the challenges identified and their novelties. Additional material can also be found in Appendix B B.1.

4.2 AIM diagram on Robust Design

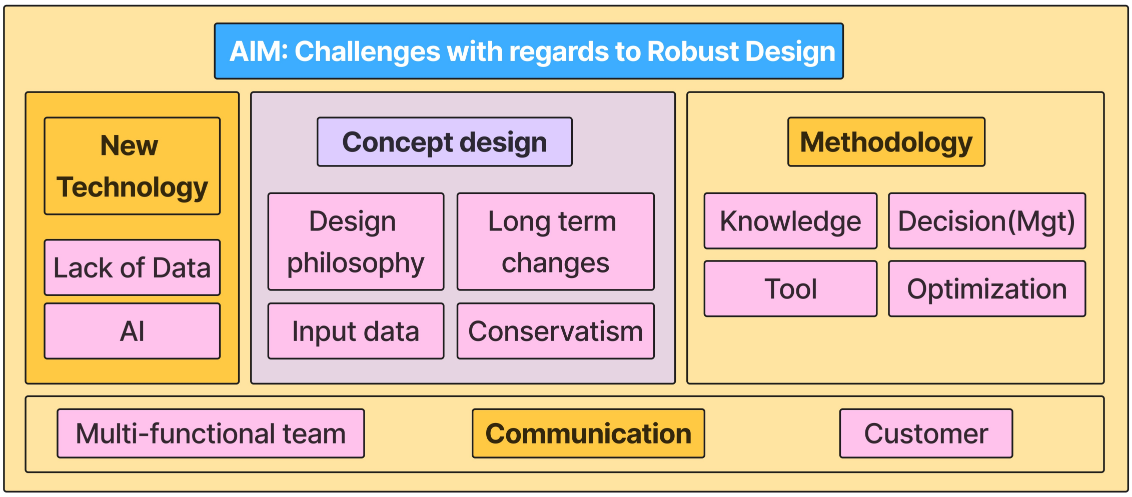


Figure 4.1: AIM diagram on Robust design

4.2.1 New Technology

Lack of data

R1.1 Over reliance on past data & R1.1 Limited past experience for predicting future robustness (AM).

Due to the plethora of data available on proven conventional methods, the industry heavily relies on the historical wealth of information. This practice is also due to the fact that both the process and product in the aerospace industry are data-driven. This creates a challenge when new manufacturing technologies such as additive manufacturing emerge in aerospace applications. Over-reliance on historical data can hinder the introduction and integration of such technologies and constrain opportunities in new products and ventures. This could ultimately slow down the overall pace of progress in the aerospace industry.

This challenge should be interpreted together with the challenge of R1.2 limited past experience for predicting future robustness which suggests that relying on past knowledge and assumptions may not always be representative of future conditions. This dependence on historical data can lead to inadequate robustness especially when future conditions differ significantly from past experiences..

R1.3 Lack of knowledge on new technologies and its merits by engineers.

This challenge could be interpreted as a resulting consequence of the challenges in R1.1 overreliance on past experience and methods. Due to this overreliance, engineers may lack knowledge of new technologies that rival existing approaches, assumptions and their advantages in achieving better robustness. They may not be motivated or incentivized to explore such technologies under time constraints since the pre-existing technology readily produces reliable products. This challenge should also be viewed in light of general industrial conservatism, driven by safety concerns.

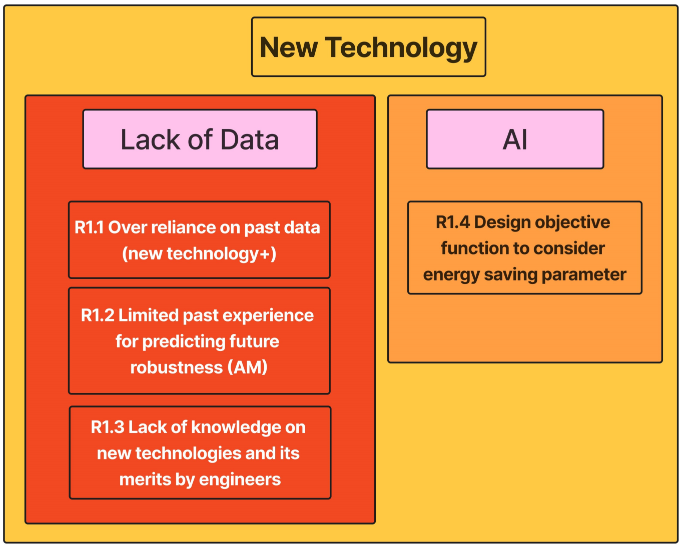


Figure 4.2: New Technology

AI

R1.4 Design objective function to consider energy saving parameter.

As the AI industry booms, enhanced computational capabilities also allow engineers to explore multiple solution paths at the cost of increased energy consumption in computation. Organizations are now considering robustness in terms of the development process by including the metric of energy expenditure. The aim can be interpreted as reducing the overall energy consumption during the stages of research, design, and product realization by exploiting new technology and strategically allocating energy resources.

4.2.2 Concept design

Design Philosophy

R2.1 Different philosophies in different phases of product development.

During different stages of product development, each functional team has its internal definition of what should be achieved and what constitutes robustness at that stage, resulting in diverse definitions. For instance, in the initial phase of product development, customer requirements and criteria are volatile (R4.3). Hence the definitions of robustness may be more aligned with the adaptability and flexibility of the development process to accommodate drastic future alterations (R2.2). At this stage, the robustness of the product development process is emphasized more than the robustness of the product itself. Regarding the product, the design philosophy tends to be more exploratory which can be drastically different from approaches in

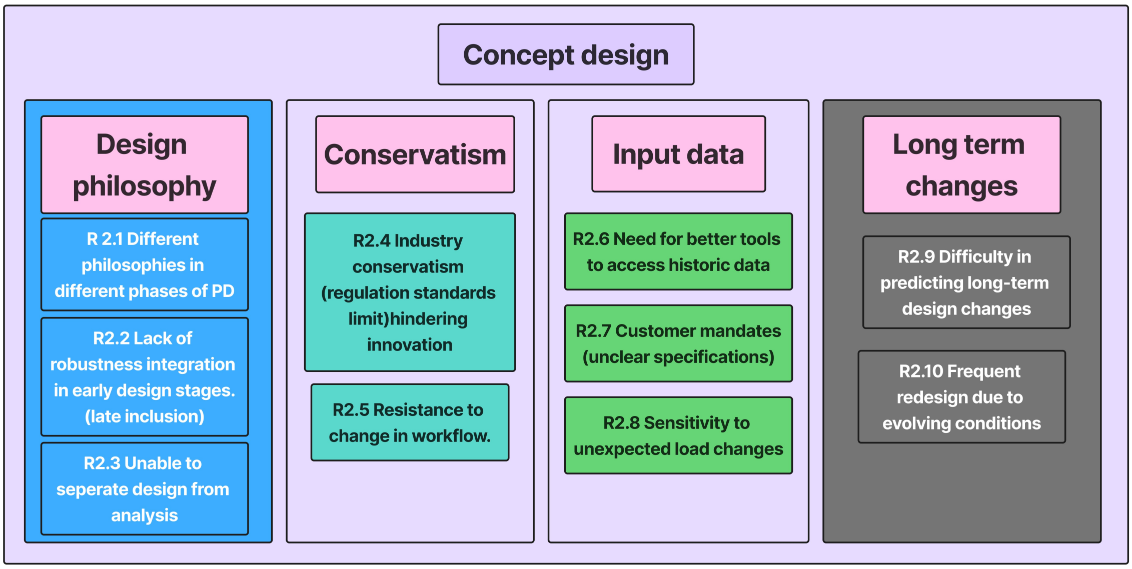


Figure 4.3: Concept design

later stages such as manufacturing and testing. This inherent diversity in design philosophy has the potential to limit cross-functional integration in design decisions (R4.1).

R2.2 Lack of robustness integration in early design stages -late inclusion.

The challenge of the lack of robustness consideration in the early stages was reiterated in multiple interviews. The robustness of the product is often overlooked in early design phases due to a focus on immediate requirements. This can be viewed as a challenge because changes to achieve robustness in later stages can become extremely difficult if provisions are not made during the initial design and planning phase.

It should also be noted that uncertainties in the initial phase play a vital role in hindering early consideration of robustness. This raises the question of whether robust optimization can realistically be considered in early phases, given the high volatility in requirements and the general lack of understanding. It is even possible that the lack of product robustness in early phases could increase the robustness of the development process itself, as mentioned in the challenge of R2.1 regarding different design philosophies.

R2.3 Unable to separate design from analysis.

Design and analysis are deeply coupled. This could be interpreted as a factor increasing the development time. Although this coupling enables more iterations, early detection of errors and increased feedback in general, if we are working with a design very similar to an existing field-approved design, this coupling can reduce efficiency and increase lead time.

Input Data

R2.6 Need for better tools to access historic data.

There is an overreliance on a very specific portion of data with the underutilization of the full knowledge available within the organization. This challenge was further observed and validated during the thesis through firsthand experience. It was noted that there is a lack of effective tools to search for pre-existing design information and standards, which can result in the duplication of a lot of engineering work. Awareness of what was done in the past regarding similar designs helps in making strategic decisions that can reduce both engineering effort and the potential for errors.

R2.7 Customer mandates (unclear specifications).

In the initial phase, customer requirements are highly volatile, making any robustness consideration difficult since early optimization may demand total redesign and reassessment as the project progresses. As the project advances, more informed judgments regarding the design can be made, making robustness considerations more practical in later stages. Unclear customer specifications or missing data complicate the robustness of the product and may lead to iterative corrections later in the process. This lack of clarity can be a major barrier to considering robustness in the early phase.

Long Term Changes

R2.8 Sensitivity to unexpected load changes.

This challenge acts as a further barrier to the integration of robustness in the early design phase. There are uncertainties in real-world conditions that cannot be foreseen or modeled in the robustness analysis. This results in elevated sensitivity to unexpected load changes, even for a robustness-optimized design which affects the effectiveness of the iterative process to achieve robustness. The variations in load can also be evolving in nature, as a function of time and working conditions, impacting the reliability and structural integrity of designs previously considered robust.

R2.9 Difficulty in predicting long-term design changes.

Initial design decisions are made with incomplete information, both in terms of customer requirements and engineering data, leading to the risk of unpredictable future modifications that require significant rework. Uncertainties in resource sourcing, geopolitics, and economic decisions can affect material selection, demanding drastic reevaluation of the design under modified material properties. These challenges are further amplified by the inherent difficulty in foreseeing all changes in later stages stemming from initial changes. The influence of environmental variations on structural integrity also plays a role in this challenge.

R2.10 Frequent redesign due to evolving conditions.

These challenges arise as the cumulative consequence of R2.7 customer mandates, R2.8 sensitivity to unexpected load changes, and R2.9 difficulty in predicting long term robustness. The initial design process does not fully account for possible variations due to the above-specified challenges and often requires modifications that can be expensive in terms of time, engineering effort, and economics. This can have a significant impact on competitiveness. The human factor, specifically employee morale should also be considered, as the repetitive nature of working on the same product can affect performance.

4.2.3 Methodology

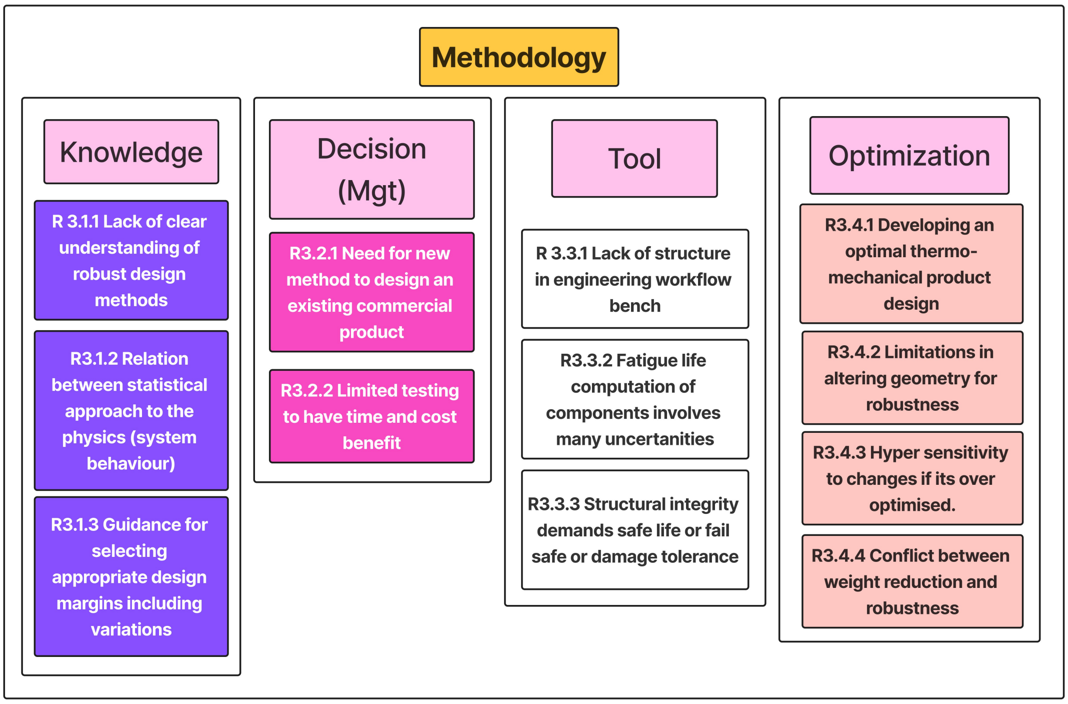


Figure 4.4: Methodology

Knowledge

R3.1.1 Lack of clear understanding of robust design methods.

It was observed that the concept of robustness is often overlooked and not explicitly verified. Based on established standards, field observations and the overall conservatism of the industry, the robustness is expected to be achieved as a byproduct of all proven practices. Consequently, there is less emphasis on robustness in individual functional areas which results in an overall lack of awareness of robust design concepts and methods to achieve it.

R3.1.2 Relation between statistical approaches to the physics (system behavior).

It is important to have a sound understanding of the physical manifestations of statistical results. In light of the challenge of R3.1.1 lack of understanding of robust design methods, a disconnection and weak understanding of how statistical methods relate to actual physical behavior can result in misinterpretation of statistical results. This can lead to misjudgment of how variations affect performance and overestimation of robustness, thereby increasing risks. The concept of robustness is not only about achieving nominal values in simulations but understanding the physical behavior helps in making practical judgments further along in the development as well as use stages, rather than blindly accepting results as the product of a black box operation.

R3.1.3 Guidance for selecting appropriate design margins including variations.

One popular approach for achieving robustness is by including additional allowances in the form of design margins. There are preexisting margin guidelines, but the validity of these can be questioned under changing real-world working conditions and novel manufacturing methods. Too much margin can result in lowered performance in exchange for safety and vice versa. Hence, it is a widespread industrial challenge to establish and maintain suitable guidance for selecting margins that account for changes in technology and environment, ensuring product reliability is maintained.

Decision

R3.2.1 Need for new method to design an existing commercial product.

In the current workflow, robustness is less emphasized. Hence to consider robustness, new approaches and methods have to be introduced into the current design procedures.

R3.2.2 Pressure to reduce design time and costs. (Testing)

The pressure of design time and cost can reduce the hours spent on new projects, which has the potential to negatively impact design quality and robustness. This should be interpreted in light of the challenge of resistance to change in workflow as well. Additional robustness analysis can increase engineering resource demands which makes the changes practically difficult to incorporate into the current workflow. These challenges can further result in limited testing to save time and cost, which in turn affects the verification of design robustness.

Tool

R3.3.2 Fatigue life computation of components involves many uncertainties.

Robustness computation of a complex multidisciplinary product can involve a high number of parameters and uncertainties. This can result in a significant increase in computation time for robustness verification. This contributes to the overall increase in the complexity of product development. This challenge was particularly discussed in the robustness evaluation regarding fatigue life since prioritizing uncertainties in fatigue life evaluation is explained as a difficult task.

R3.3.3 Structural integrity demands safe life or fail safe or damage tolerance.

Robustness demands certain allowances and margins, which can result in increased mass and thus act as a limiting factor for finer optimization. Including additional robustness will require a trade-off between the aerospace interest in mass reduction for fuel efficiency and the design interest in adding more material in specific regions to ensure robustness.

Optimization

R3.4.2 Limitations in altering geometry for robustness.

There is very limited freedom in altering the geometry, primarily due to R2.7 customer mandates and even as an unintended byproduct of strict regulations. Weight reduction is also considered a primary constraint that limits the freedom to modify geometry to improve robustness. This creates a trade-off between making designs structurally sound and keeping them lightweight. The limitation can be further justified by situating the components within the overall system. Alteration of one component can affect the packing efficiency and relatively impact the geometric requirements of adjacent components.

R3.4.3 Hyper sensitivity to changes if it's over optimized.

Due to the wealth of data from previous experience in designing and field data, engineers can grow confident in the uncertainties and parameters considered. This can result in over-optimization of similar designs that can make the design hypersensitive to any changes deviating from previous assumptions. This hypersensitivity, if accumulated, can demand redoing the entire structure and material selection. This can also be reasoned as a case against strict robustness optimization at the early phase. It also raises a degree of concern in optimization, questioning whether the additional allowances which are often overlooked as inefficiencies, unintentionally account for robustness against unknown unknowns.

R3.4.4 Conflict between robustness and optimization.

Robustness often demands more material in critical areas, whereas minimizing the weight of the component is a common requirement in aerospace due to the impact of additional weight on fuel economy. Hence, the tradeoff between designing for robustness (quality) and optimizing for weight and cost can be viewed as a perpetual challenge throughout the history of aerospace.

4.2.4 Communication

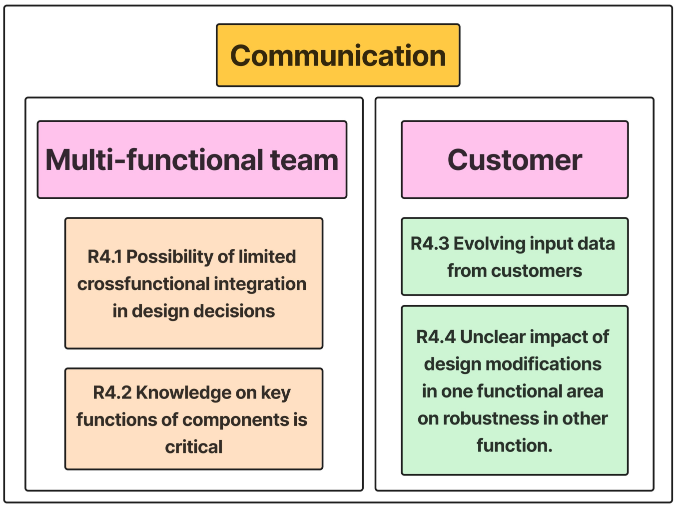


Figure 4.5: Communication

Multi-functional team

R4.1 Possibility of limited cross functional integration in design decisions.

Different functional areas make design decisions in silos under different design philosophies, which can lead to misalignment and inefficiencies in the overall system. The concept of robustness should be considered as the overall quality of the system and not limited to one specific area. Conflicting demands in each aspect of engineering give rise to difficult tradeoffs, where a factor contributing to robustness in one functional area acts as a barrier to achieving robustness in another. For instance, robustness in manufacturing and structural engineering may demand fewer sharp bends, while the same would be a desirable quality from an aerodynamic perspective. Along with this barrier, the human factor of diversity in training can make cross-functional integration practically hard to achieve. This makes it challenging to understand the criticalities in one functional area from another R4.2, resulting in difficulties in managing and making informed strategic decisions and tradeoffs.

Customers

R4.3 Evolving input data from customer.

The design process is impacted by late-stage changes in customer-provided data, leading to unpredictable design adjustments. This affects the optimization of based on thermal loads, material choices, and mechanical constraints. While this feedback loop is important for producing better products, from the perspective of robustness, the analysis must be performed with each update which demands further computations and leads to higher lead times.

R4.4 Unclear impact of design modifications on robustness.

This challenge stems from the uncertainty regarding how design changes such as thickening materials affect the robustness objective from another functional area. The robustness optimization of the structural aspect of the design cannot be used to intuitively predict the impact on robustness from the perspective of thermal or aerodynamic loads. This challenge could possibly be managed by optimizing robustness under the combined consideration of loads from multiple disciplines. However, this drastically increases computational complexity and resource demands. Comprehensive analyses of this kind are difficult to achieve due to the level of cross-functional collaboration required, management of conflicting demand, use of different software tools across functional areas and limitations in computational resources and capabilities.

4.3 AIM diagram on Uncertainty

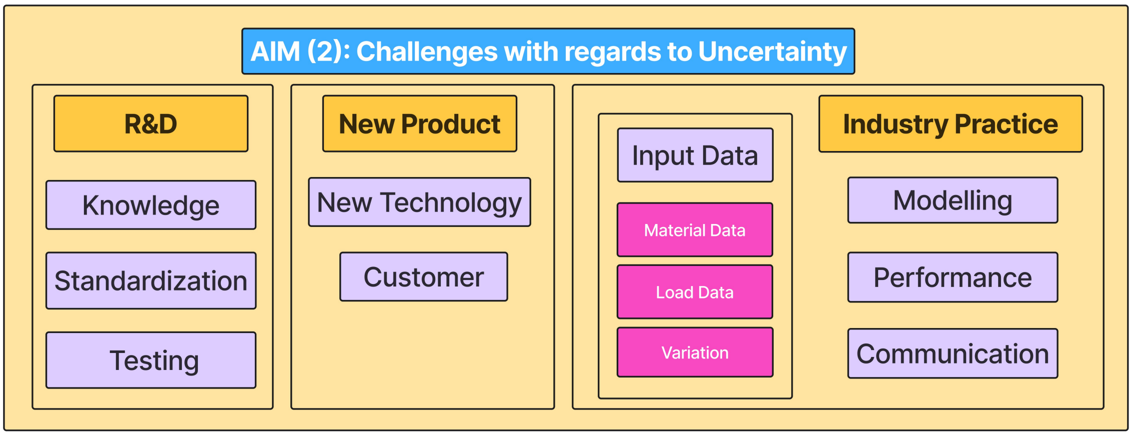


Figure 4.6: AIM diagram on Uncertainty

4.3.1 Research and development

Knowledge

U1.1.1 Limited awareness and training in uncertainty quantification methods

Aerospace design requires probabilistic models to accurately assess risk factors since the probabilistic conditions better represent the variations expected in the real world. Many engineers are familiar with deterministic approaches but not with probabilistic tools or other uncertainty quantification methods and even fewer have received formal training. This lack of awareness can limit the effectiveness of uncertainty analysis.

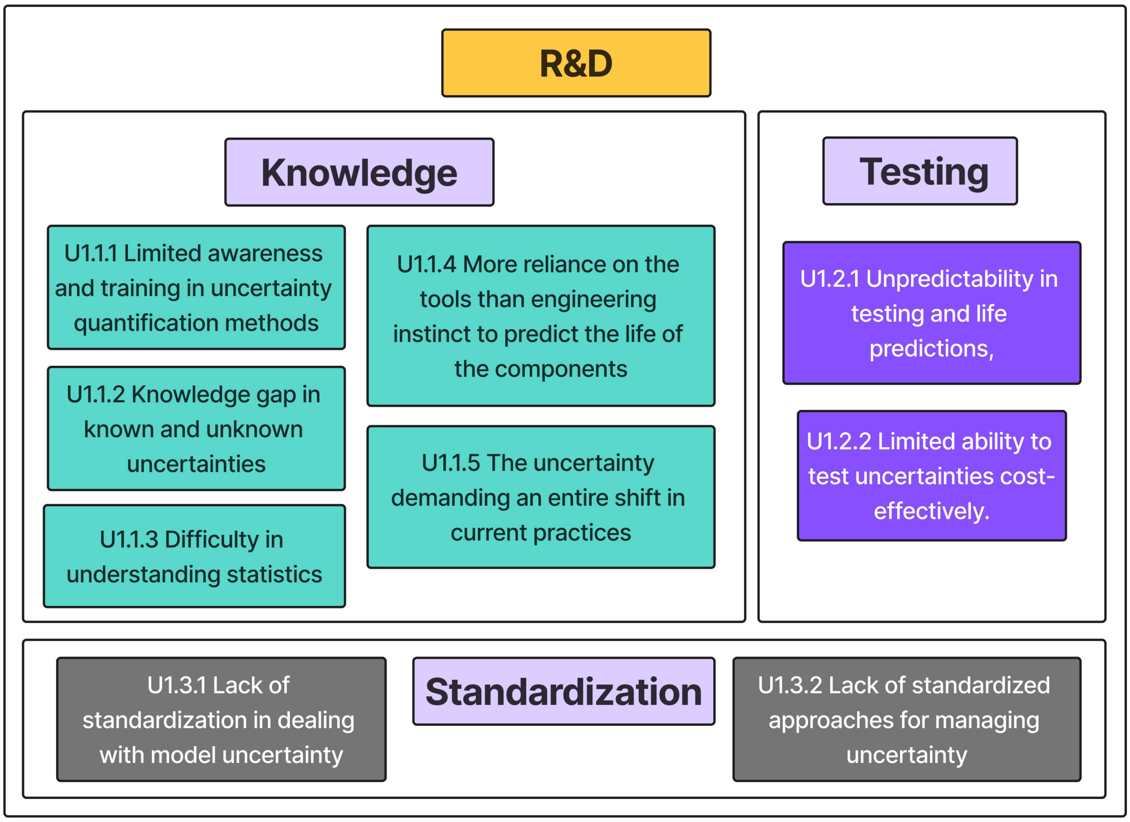


Figure 4.7: Research and Development

U1.1.2 Knowledge gap in known and unknown uncertainties.

In real-world settings, due to the inherent nature of some uncertainties, their impacts are hard to determine. In the current paradigm, known uncertainties that are quantifiable to some extent dominate the analyses. All the uncertainties, according to which the models are evaluated for robustness are predominantly of this nature. The lack of knowledge, along with cumulative and emergent behaviors constituting unknown uncertainties can affect the design's robustness and increase unpredictability in real-world scenarios. This concern is further echoed in the challenges of U3.1.1 uncertainties from external factors and U3.1.2 evolving load uncertainty over time.

U1.1.3 Difficulty in understanding statistics.

Real-world applications are better represented by probabilistic models than deterministic ones. However, compounded by the challenge of U1.1.1 limited awareness and training in uncertainty quantification methods, there is a pressing need to equip engineers with the skills to interpret statistical variations and translate analysis outputs into actionable engineering insights. The current disconnect between statistical knowledge and physical understanding makes it difficult to effectively apply statistical models, increasing the risk of misinterpreting statistical results.

U1.1.4 More reliance on the tools than engineering instinct to predict the life of the components.

Simulation tools are often treated as black boxes, with their outputs accepted at face value as definitive. This reliance can pose significant challenges, especially when exploring unfamiliar product designs, as it may lead to bypassing critical engineering judgment. Such overdependence becomes even more problematic in the context of black swan events [55], where unexpected uncertainties arise. Additionally, uncertainties in input data and analysis models further limit the practical confidence that can be assigned to simulation results.

U1.1.5 The uncertainty demanding an entire shift in current practices.

Traditional design approaches assume a deterministic world which is an idealized assumption made for practicality. However, incorporating uncertainty demands a shift toward resilience and a partial departure from the intuitive deterministic mindset. Conventional workflows, certification processes, and even organizational mindsets must evolve to accommodate this novel approach. This systemic inertia directly contributes to the lack of standardization in U1.3.1 and the system's inability to effectively adapt to unknowns as highlighted in U2.1.1.

Testing

U1.2.1 Unpredictability in testing and life prediction.

Even under highly controlled and identical testing conditions, specimens exhibit varied fatigue lives due to microstructural and surface inconsistencies. This variation is also reflected in U4.2.2 manufacturing variability affecting performance, making it challenging to define a single safe life. From a philosophical perspective, uncertainty encompasses not only what is unknown but also the extent to which known factors may vary.

U1.2.2 Limited ability to test uncertainties cost effectively.

Testing to quantify uncertainties is often expensive and sometimes economically unfeasible because capturing these uncertainties requires large sample sizes and extensive test setups. This cost constraint can push teams to rely on assumptions instead of conducting thorough empirical validation, fostering an illusion of certainty. It is a valid question to ask how much deeper analysis can be justified when weighing cost versus benefit. Such financial limitations can undermine the ability to validate probabilistic models, impacting the reliability of factoring and ranking uncertainties as discussed in U4.1.3.

Standardization

U1.3.1 Lack of standardization in dealing with model uncertainty.

While mathematical models are employed to manage uncertainty, there is no universally adopted industry standard among stakeholders. This results in variations in how different teams address uncertainties, introducing systemic inconsistencies and leading to conflicting safety margins across a product. This issue particularly impacts communication channels, reinforcing the existing challenge of U3.2.2 difficulty in systematically communicating uncertainties across departments.

4.3.2 New product

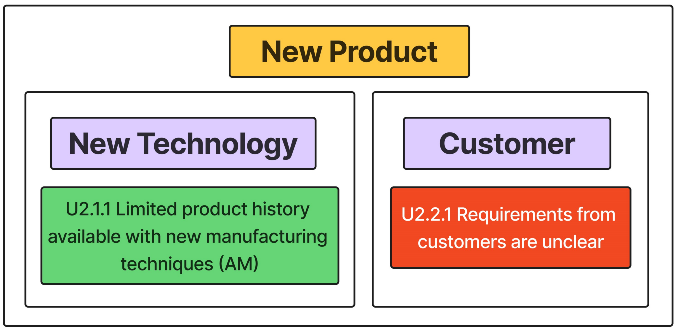


Figure 4.8: New product

New Technology

U2.1.1 Limited product history available with new manufacturing techniques (AM)

Traditional manufacturing methods like forging and casting have well-documented uncertainties, whereas additive manufacturing is relatively new which makes the uncertainties difficult to quantify. Novel production methods introduce additional process-related anomalies and uncertainties, which complicates defining robust material allowable U3.2.2. The lack of historical data also challenges the modeling of performance U4.2.1 by creating ambiguity around which uncertainties should be included in the analysis. This pattern of over-reliance on historic practices and data is a recurring theme throughout the qualitative analysis conducted in the thesis.

Customer

U2.2.1 Requirements from customers are unclear- Customer practices

Customers rarely quantify risks explicitly and different customers often perceive or communicate risks in varied ways. Uncertainties in external load conditions are frequently not effectively conveyed during the initial stages, making it challenging for engineers to accurately assess the true design risks. This disconnect compels engineers to make assumptions about what to simulate, which can lead to errors, as reflected in the challenges of U3.1.1 regarding uncertainty from external factors.

4.3.3 Industry practice

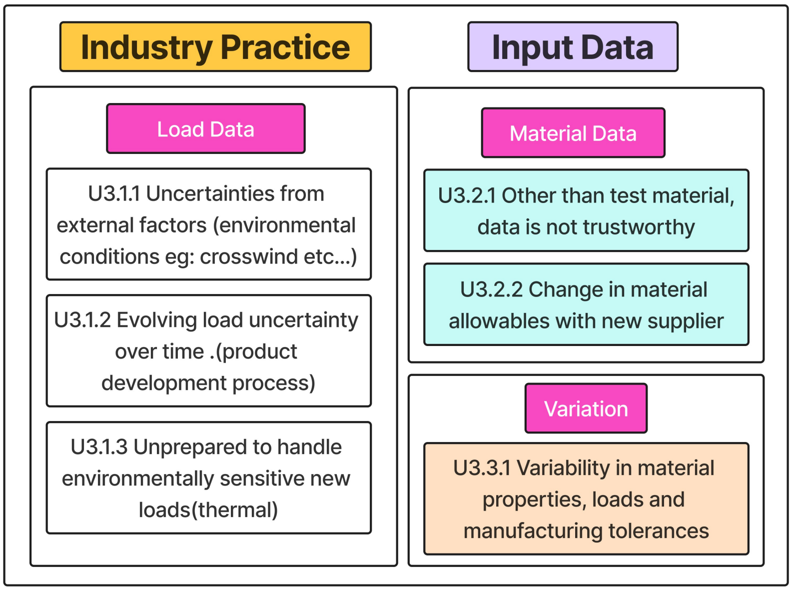


Figure 4.9: Industry practice I

Load data

U3.1.2 Evolving load uncertainty over time. (product development process)

Initial design load assumptions often fail to capture the real-world conditions experienced after deployment. The rigidity of these early assumptions makes it difficult to incorporate updates as new information arises. Predicting how load conditions evolve over the product lifecycle including during the development stage, remains a significant challenge. As field data accumulates, initial load assumptions can become outdated which results in discrepancies between predicted and actual operating conditions.

U3.1.3 Unprepared to handle environmentally sensitive new loads (thermal)

It is impractical to incorporate all parameters into a single model, necessitating the ranking and prioritization of certain loads and uncertainties. However, traditional approaches often fail to capture or predict coupling effects arising from the accumulation of minor, unranked uncertainties.

Variations

U3.3.1 Variability in material properties, loads and manufacturing tolerances

Engineers face the critical decision of whether to design using average material properties, which supports mass minimization, or to optimize for the minimum properties to ensure safety. This duality in design philosophy reflects differing tolerances to uncertainty. Changes in material supply can cause variations in mechanical properties, necessitating costly and time-consuming re-qualification processes. Such unpredictability negatively impacts the overall robustness of the product. This issue is also highlighted in challenge U3.2.2 regarding changes in material allowable with new suppliers.

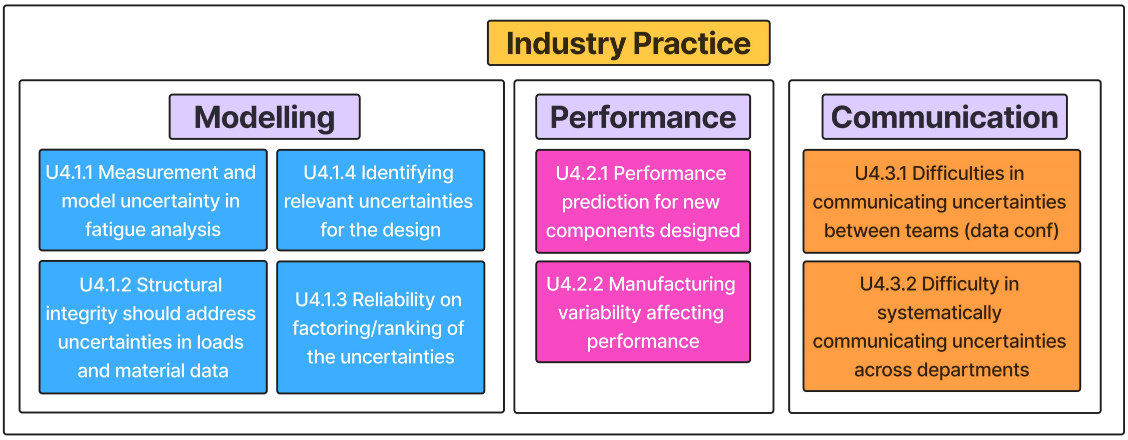


Figure 4.10: Industry practice II

Modelling

U4.1.3 Reliability on factoring/ranking of the uncertainties.

A significant challenge lies in ranking and identifying relevant uncertainties, especially in new product development. Determining which parameter uncertainties to include in the analysis and prioritizing the most impactful factors is difficult without deep domain expertise. This can be further challenging in novel product realization processes such as additive manufacturing (U1.1.1) and reliable data from functional areas (U3.2.2). This uncertainty can lead to inefficient use of resources by focusing on trivial effects. The challenge U4.1.4 highlights the lack of clear guidance in identifying critical uncertainties, which may cause engineers to either over-design components or unintentionally overlook key risk factors in the absence of prior experience.

Communication

U4.3.1 Difficulties in communicating uncertainties between teams (data confidentiality)

Even when approved data is available, ensuring transparency regarding the sources of uncertainty remains an ongoing challenge. Varying levels of confidentiality across projects often restrict the sharing of critical information, even within different sectors of the same organization.

U4.3.2 Difficulty in systematically communicating uncertainties across departments.

The absence of systematic communication channels between functional areas poses a significant challenge in effectively conveying uncertainties. Engineers typically rely on established design practices and apply safety margins to address these uncertainties. However, the combined effectiveness of these measures often goes unchecked due to limited cross-functional communication. While this siloed approach may be seen as a practical means to streamline workflow, it also adds to the problem by creating data and linguistic barriers, leading to inconsistent handling and interpretation of uncertainties across departments.

4.4 AIM diagram on Design Margins

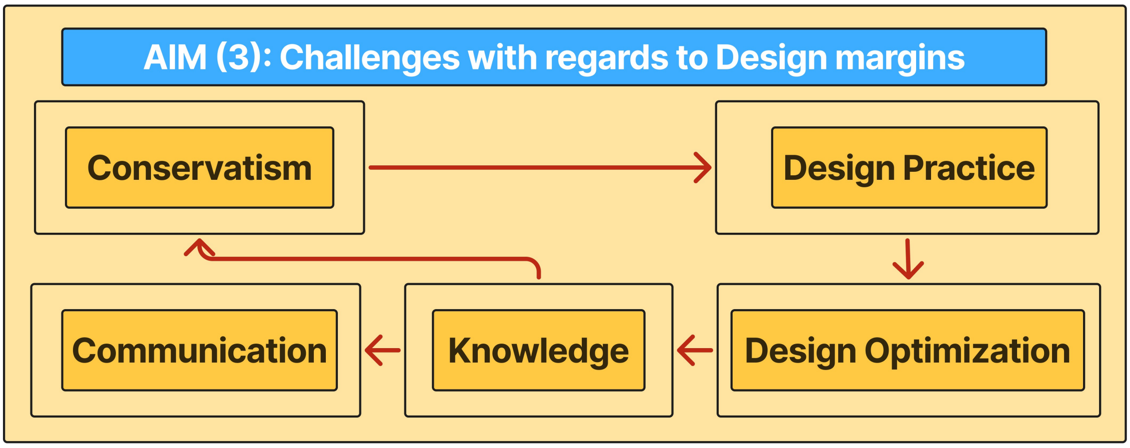


Figure 4.11: Design margin

4.4.1 Conservatism

Conservatism emerged as a prevalent theme throughout the interview analysis, particularly in the context of design margins. To better understand engineers' perspectives, the study further explored how conservatism influences design margins and its potential consequences. Literature indicates that design margins are a widely used method to provide safety buffers that accommodate variations and uncertainties, thereby enhancing the robustness of designs. At the same time, concerns about overdesign were evident, prompting the inclusion of this concept in the qualitative data collection. It is important to clarify that the AIM challenges referencing overdesign do not confirm its presence within the organization; rather, they reflect an awareness of its potential consequences and suggest that overdesign could occur if there are no active mechanisms to prevent it.

D1.1 Overly conservative margins leading to inefficiencies

These challenges reflect the deeply ingrained industry practice of applying generous design margins to ensure safety and meet certification requirements. Given the critical need for safety and reliability in aerospace components, engineering concepts such as factors of safety and design margins are routinely employed to account for uncertainties. However, this often leads to designs that exceed actual performance demands. The added robustness typically increases the mass of components, which can negatively impact fuel efficiency and thus run counter to the industry's sustainability goals. This raises an important question: do conservative margins always

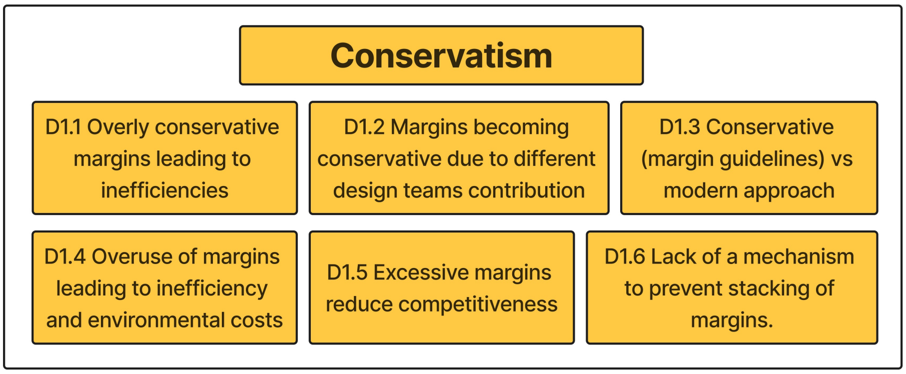


Figure 4.12: Conservatism in design margin

result in a "good" design when fuel economy carries significant weight in defining design success? This concern is closely related to the challenge D1.4 regarding the overuse of margins leading to inefficiency and environmental costs.

D1.2 Margins becoming conservative due to different design teams contribution.

Design margins are not managed or applied within a single design unit but are distributed across multiple functional areas, including planning, design, testing and manufacturing. Each team often applies its own set of margins, frequently without coordination or communication. This cumulative effect can lead to excessive conservatism layered on top of the already prevalent industrial conservatism in aerospace. This challenge is closely related to D4.3 limited awareness of margin factors across functions. The lack of visibility into the rationale behind margins applied by other teams results in redundant safety layers, which ultimately make the final design unintentionally inefficient.

D1.6 Lack of a mechanism to prevent stacking of margins.

This challenge arises from the combined effects of D1.2 conservative margins contributed independently by different design teams, and D4.3 limited cross-functional awareness of margin factors. Safety layers accumulate as each team applies its own margins without realizing that other teams have already accounted for similar uncertainties. Since margins originate from various functional areas, each area employs domain-specific terminology and approaches. It becomes difficult to identify and prevent margin stacking. The investigation revealed that multiple design margins may result in an increase in component thickness, yet no proactive mechanism was found to verify whether these margins overlap or compound unnecessarily. This suggests a potential for overcompensation, presenting a valuable hypothesis for further study to uncover optimization opportunities within the organization.

4.4.2 Design practice

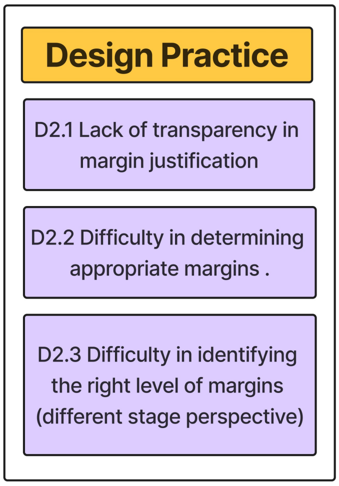


Figure 4.13: Design practice

D2.1 Lack of transparency in margin justification.

Engineers often inherit margin values from established design practices and legacy projects, treating them as rules of thumb without fully understanding the original rationale behind their derivation. This challenge compounds D1.2, where margins become increasingly conservative due to contributions from various design teams. These are drawn from diverse sources such as regulations, internal best practices and customer requirements. The lack of transparency around the origin and justification of these margins makes it difficult to evaluate whether they remain appropriate, resulting in margins that may be either overly conservative or insufficient. It should be noted that, while margin values at different design stages are often documented, the underlying factors and assumptions used to develop these values tend to be less intuitive and poorly communicated.

4.4.3 Design optimization

D3.2 New design concepts need extensive testing.

When exploring new product designs manufactured through novel techniques, extensive testing is essential to establish optimal design margins. Due to the lack of historical data for these new materials and processes, extensive validation is required to ensure safety and robustness. However, this level of testing significantly increases development time and costs, often discouraging adoption. This barrier is further reinforced because the investment rarely yields immediate returns, making the process less attractive to stakeholders.

D3.3 Hard to balance safety margins and performance constraints.

Given that existing conservatism can adversely impact efficiency, the core challenge lies in finding an optimal margin that maintains robustness without incurring unnecessary weight penalties. While striving for this balance is desirable, achieving it in

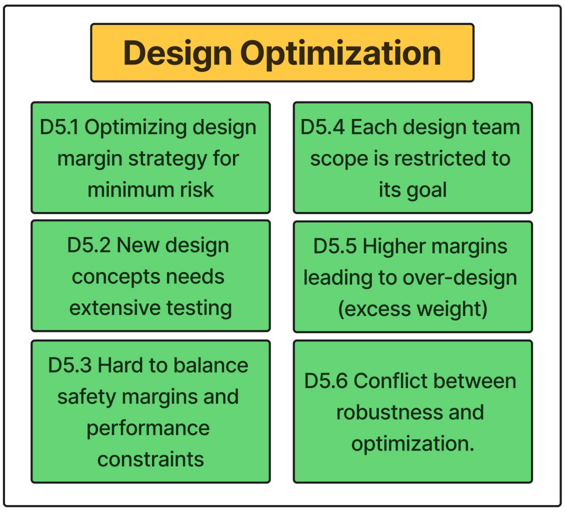


Figure 4.14: Design optimization

practice remains difficult. This challenge closely relates to D3.6 the conflict between robustness and optimization where design margins intended to ensure reliability often result in increased weight, posing a trade-off between safety and performance.

D3.4 Each design team scope is restricted to its goal.

Under the paradigm of constrained time and delivery pressures, teams often prioritize their own functional area and performance metrics rather than focusing on system-level optimization. This siloed approach can improve individual team efficiency but may compromise the overall performance of the final product. This issue also affects design margins, as highlighted by challenge D1.6 the lack of mechanisms to prevent margin stacking arising from multidisciplinary contributions.

D3.5 Higher margins leading to over-design (excess weight).

Higher design margins used to address uncertainties often lead to over-design and unused capabilities. Designers apply large safety margins to compensate for unknowns, resulting in components with excessive performance capacity. However, even when these extra capabilities are acknowledged, the limitations in other system components can act as bottlenecks that prevent full utilization.

4.4.4 Knowledge

D4.2 Limited transfer of knowledge from expert to new engineers.

New engineers often struggle to understand how design margins are determined and applied because this knowledge is typically acquired through experience rather than formal training, given the tacit nature of margin-related decision-making. Time constraints further hinder effective knowledge transfer to new employees, leading to the blind adoption of design margins without fully grasping their rationale. It's a challenge for organizations, to demand better knowledge capture tools and systems

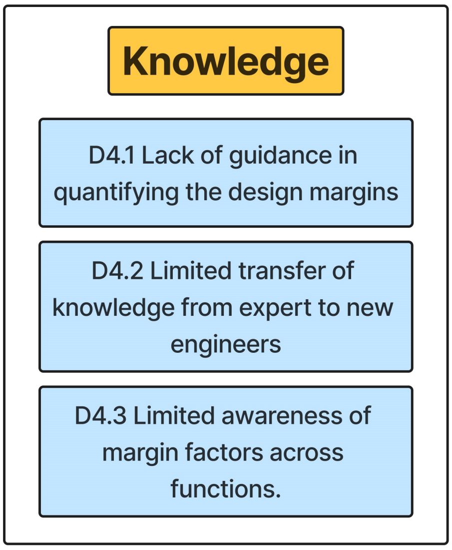


Figure 4.15: Knowledge

to preserve this critical know-how.

D4.3 Limited awareness of margin factors across functions.

This challenge stems from the previously discussed factor D3.4, where each design team's scope is limited to its specific goals. As a result, considerations are not always effectively communicated across teams which leads to redundancies in margin application. While information may be available on demand, investigations revealed that the origins of many margins are difficult to trace. In practical terms, it is often unrealistic to expect engineers to undertake such extensive investigations during the design process.

4.4.5 Communication

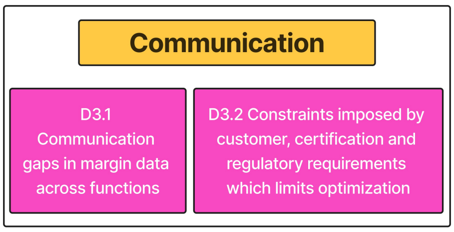


Figure 4.16: Communication

D5.2 Constraints imposed by customer, certification and regulatory requirements which limits optimization.

In addition to conservative and stringent regulatory requirements imposed by governing bodies, margin requirements are often dictated by customer specifications. These ingrained industrial practices and customer mandates are difficult to challenge. This further limits the opportunities for margin optimization. Even when engineers possess the capability to optimize margins, they remain constrained by nonnegotiable certification criteria. This rigidity discourages exploration and innovation and often leads to stagnation in advancing more efficient or novel design approaches.

4.5 Results & Discussions

The analysis of the combined qualitative data from the AIM diagrams, focusing on the themes of robustness, uncertainties, and design margins revealed that the challenges are inseparably interconnected. A recurring observation was that many design choices, while rooted in established conservative practices, are frequently influenced more by organizational behaviors and culture than by a clear and informed understanding of actual variation or risk.

4.5.1 Design margin & Safety related insights

While achieving a safe design remains a shared priority across teams, the methods through which those are achieved are through conservative assumptions and design margins often lead to unintended consequences. These practices can undermine efficiency and pose challenges to achieving true robustness from both the product and process perspectives.

A significant issue observed that could be explored further was the widespread use of defined margins which might be conservative. Each team operates with its own assumptions, uncertainties and constraints with limited inter-functional communication possibilities. This opens the possibility that each of them apply buffers to manage their localized uncertainties. This possibility of stacking margins is rarely challenged, primarily because there is no systematic mechanism to trace their origin or quantify their cumulative impact.

Although each of the individual considerations of margins at each functional area is justifiable, these factors have the potential to be often compounded hence demanding a unified and centralized management strategy. As a result of the lack of such system-level considerations, the final product may end up over-designed, heavier and costlier than it needs to be. This tendency can potentially cause misalignment of the design process with the sustainability objectives in the industry(D1.4,D1.5).

4.5.2 Industrial Conservatism

To exemplify this potential of the stacking effect, within the investigation of the design practices, factors such as casting factor and knockdown factors were observed to be specified. These elements inherently can result in the increased thickness of the design, but it was not evident that their combined effect was either evaluated or optimized.

It should be also considered that the inherent industry conservatism (D5.2) demanding the strict adherence of such prescribed margins for the approval and certifications also hinders innovation discouragement of any proactive margin management initiative.

Even though the marginal values are specified in design practices, the limited transparency in how margins are justified still persists. These values in the design practices are often rooted in industrial standards or the best practices within the organization based on successful projects. This factor makes it difficult to adapt to new contexts or account for changes in materials, processes, or operational conditions.

4.5.3 Trade offs related insights

The above-discussed barriers also lead to inconsistencies in how performance tradeoffs are managed. The additional buffer result from unintentional accumulation may masquerade as nonnegotiable requirements. Such rigidity further increases the preexisting conflict between the need for safety and weight optimization demand (D3.3, D3.5).

Without the ability to accurately model these tradeoffs against real-world uncertainties, teams often opt for approaches with increased conservatism. This may offer apparent safety but introduces inefficiencies that cascade through the system.

It must be also reflected upon the possibilities that the unintended overalls of excess provide some degree of resistance towards the sensitivity to unexpected load changes (R2.8) and unidentified unknown or less precise knowns.

4.5.4 Uncertainties and new technologies

These challenges become more pronounced when dealing with newer technologies such as additive manufacturing, where historical data is limited (R1.2, U2.1.1). New manufacturing approaches introduce unique process-related variations that are not easily captured or compensated by using fixed margins. This situation also provides an opportunity to introduce a marginal management structure without the need to challenge the existing standards. In the lack of it, engineers may make speculative and often conservative assumptions under tight project timelines and budgets (R3.2.2,U1.2.2).

4.5.5 Barriers to early robustness thinking

The industry's existing conservatism in adopting new design or analysis methods (R2.4, R2.5) further complicates the integration of robustness thinking at earlier design stages. The volatile nature of customer requirements (R2.7) especially at the initial stages and limited access to reliable data on long-term load conditions (R2.9, U3.1.2) further erode the ability to make robustness informed decisions early on the design phase. Consequently, robustness is often approached reactively, once detailed designs are already in place making any redesign effort both costly and organizationally difficult.

4.5.6 Limitations of deterministic mindset

Real-world uncertainties such as variability in material properties (U3.2.1), load conditions (U3.1.1) or fatigue behavior (R3.3.2) are inherently stochastic and are not fully accounted for with deterministic analysis methods. The deterministic approaches of treating the load and limiting constraints are singular values that are an unreliable oversimplification of variability. This approach remains dominant in most workflows. The capacity of such an approach to reflect the full range of variability seen in real operational contexts is extremely limited. This existing gap in representation contributes to the issue, and results in either underestimation or overestimation of design robustness, as uncertainties are either oversimplified or ignored (U1.1.2, U1.1.5). The lack of tools and training for probabilistic thinking (U1.1.1, U1.1.3) reinforces this reliance on conservative paths of working and thought process.

4.5.7 Need for a structured robustness framework

In these contexts of discussions, the problem is not that engineers are unaware of variation, but that the existing tools and workflows are not designed to work with it explicitly. These issues that the current methodology not being representative of expected uncertainties point toward the need for a more structured and probabilistic approach to design robustness and reliability. Evaluating robustness under parameter uncertainty can help resolve many of the interconnected challenges that surfaced in the qualitative study. Engineers can use such approaches to identify which parameters contribute most to robustness variation which makes optimization efforts more targeted and informed.

‘

4.6 Conclusion

The emerging results from the qualitative analysis clearly demand a shift toward a robustness analysis framework that is both probabilistic and computationally enabled. The nature of the challenges of uncertain load conditions, variability in material, manufacturing processes, absence of standardized margin practices, and limited data on new technologies all converge on a shared need for the ability to understand and manage variation, rather than simply guarding against it through conservative assumptions. By embedding such into the design process, there is a potential to move beyond the legacy constraints and toward a design culture that is safer and more adaptive to modern change. Additionally, the pressure to reduce lead time in engineering projects (R3.2.2) makes it increasingly important to streamline robustness evaluation workflows.

In this regard, tools like Ansys OptiSLang offer a relevant computational pathway that is not a replacement for engineering judgment, but an enabler of more informed and transparent decision making. The strength of such an approach lies in its ability to simulate and explore variability directly. In contrast to deterministic models that evaluate a single outcome, probabilistic analysis enables the investigation of how a design performs across a range of scenarios defined by variations in load, geometry, material properties, and even variabilities in performance thresholds.

Computational capabilities of variance-based sensitivity analysis directly address the challenge by finding a reliable way to rank the contribution of uncertainties by each parameter U4.1.3, U3.1.1. Thereby offering a structured basis for targeting optimization efforts. This is directly relevant in contexts where current practices rely on intuition or historical precedent, especially in the absence of data. Additionally, the ability to define not only input parameters but also limit states as probability distributions enable a more realistic and data-driven assessment of system-level reliability something not feasible with traditional methods. Limitations in altering geometry for robustness R3.4.2 is a major hurdle that could be handled better by limiting the design space for the sampling for optimization.

In summary, the study highlights that robustness cannot be an afterthought and must be embedded within the design logic. In the current paradigm of the complex aerospace design landscape, this increasingly means designing with uncertainty.

5

Quantitative Study

5.1 Introduction

This chapter discusses the computational backbone of the thesis through the results of variance-based optimization and verification. The study seeks to achieve a balance between mass reduction without compromising structural safety. This is achieved with the aid of the platform of Ansys OptiSLang to embed robustness and reliability into the very fabric of the design as illustrated in the Figure5.1.

In the quantitative study, robustness optimization of two different models, namely steel hook and lug, was conducted. The initial investigation involved a parameterized static structural analysis of a hook geometry made from structural steel. Both the conventional iterative approach for optimization and the novel single-cycle approach enabled through the integration of probabilistic VMEA are explored using the hook model. The novel approach is hypothesized to have made this process more computationally efficient. The detailed probabilistic analysis of steel hook can be found in appendix C C.2. With the hook study establishing a methodological baseline, the same methodology was applied to a simplified aerospace component, referred to hereafter as the “Lug”. It should be noted that the optimization cycles explored in the thesis are reactive steps to achieve robustness due to the failure to arrive at a suitable design point in the previous optimization. The following sections present the results and analysis from both the studies.

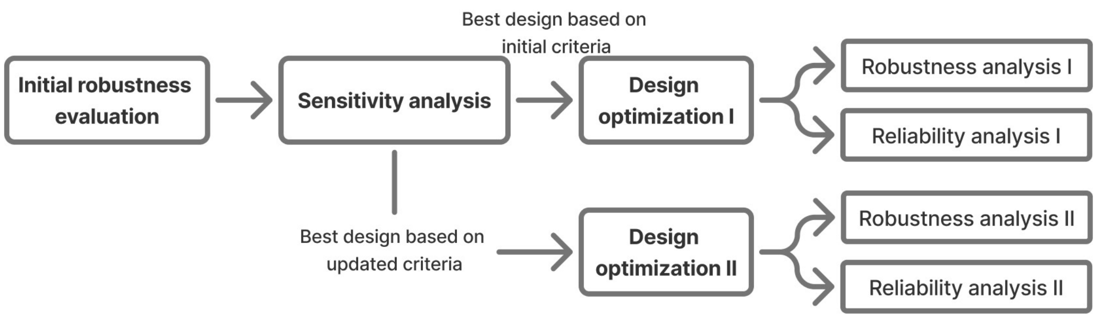


Figure 5.1: OptiSlang flowchart

5.2 Probabilistic analysis of lug using OptiSLang

The current phase of the study involved performing robustness optimization on a simplified lug geometry using the Ansys OptiSLang workbench. The geometry and loading conditions are intentionally simplified and based on assumptions to demonstrate the methodology while respecting intellectual property rights. Consequently, the geometry considered in this study is based on the research article [56], with structural steel selected as the material. The OptiSLang workflow employed in the optimization of the lug is illustrated in Figure 5.2.

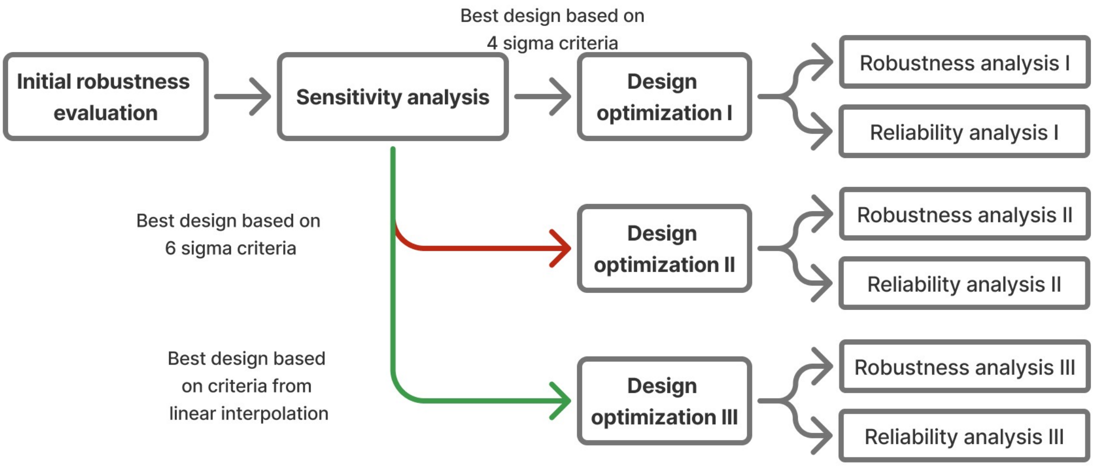


Figure 5.2: OptiSLang workflow of lug

5.2.1 Requirements and initial setup

- Objective of minimizing the mass
- The maximum stress should not exceed 300 MPa.
- Robustness requirement: The optimal design should ensure that the failure stress limit stays outside the 4.5 sigma safety margin.

Geometric constraints

Requirements	**Reasoning**
Base thickness has to be unaltered (20mm)	Minimum dimension due to holding requirement – Fixed support
Minimum of 16 mm from the hole center to the bottom fillet should be maintained	Clearance from tightening elements
Maintain minimum of 8 mm height from Base to side profile	For base strength – User demand
Diameter_of_hole shouldn't exceed 16.018 mm	Assembly requirement – User demand

Model

The nominal geometry of the lug is illustrated in Figure 5.3. These figures also highlight the geometric parameters used in the analysis. The nominal values for these parameters are summarized in Table C.8.

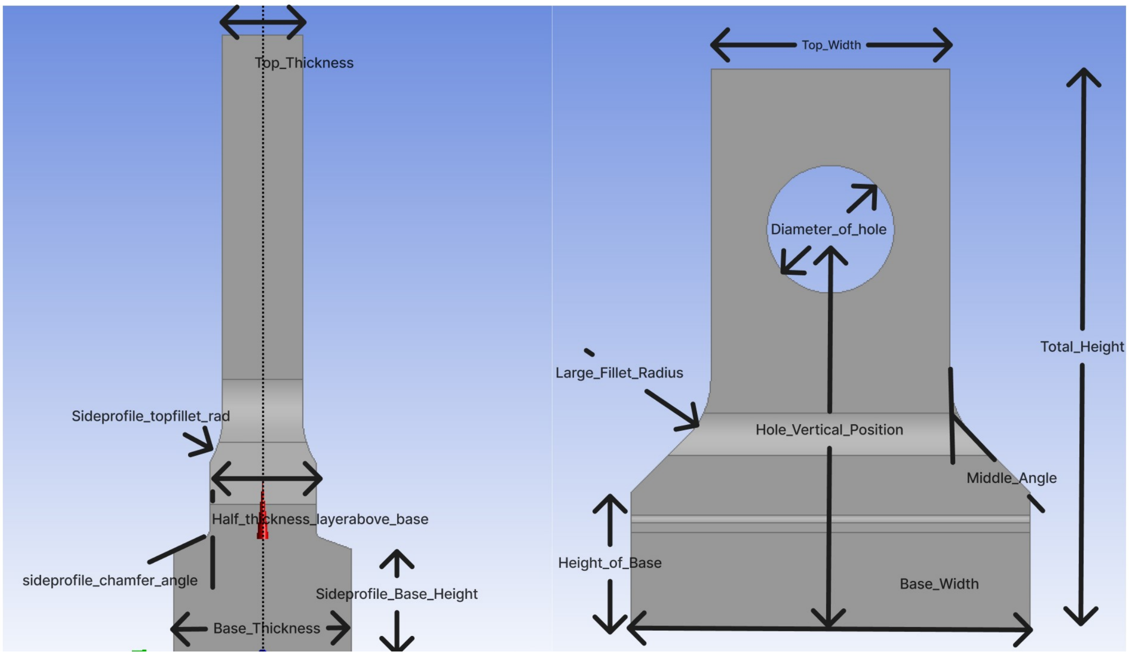


Figure 5.3: Front and side views of nominal lug

Boundary condition

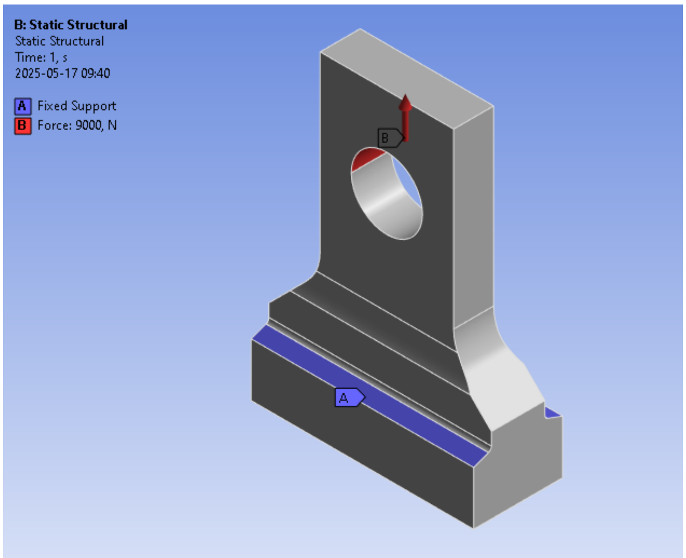
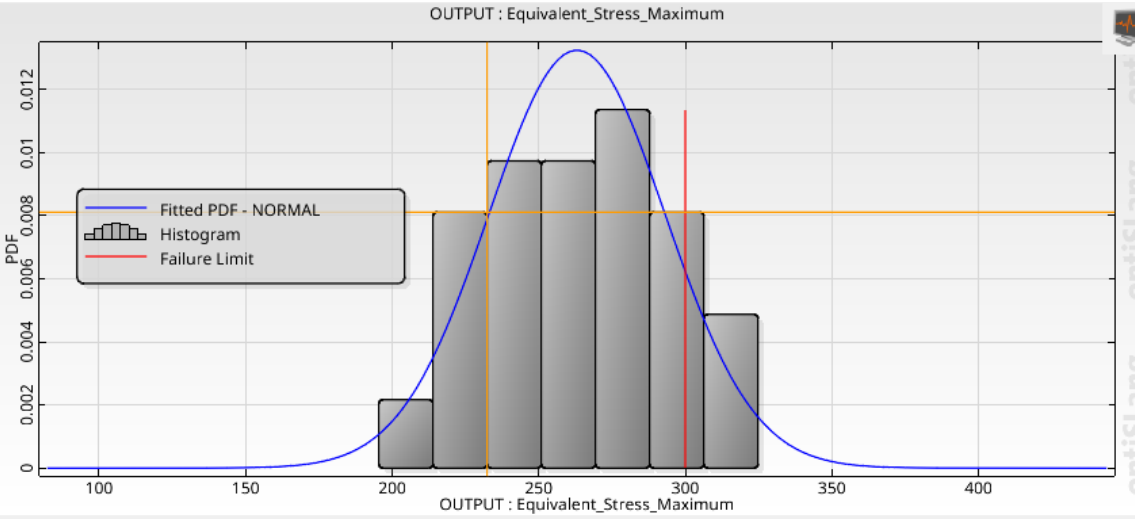


Figure 5.4: Fixed support and tensile load of lug

A global mesh with an element size of 1 mm was applied to the model. The lug is subjected to a tensile load of 9000 N, applied vertically on the upper half of the hole, while the bottom is fixed as illustrated in Figure 5.4. These boundary conditions were chosen in the interest of maintaining consistency with the setup described in the article [56].

The responses selected for analysis are the geometric mass and the maximum equivalent stress.

5.2.2 Robustness evaluation of the initial design



Hide Statistical data

Fitted PDF : NORMAL			
Statistical Moments		Parameter	
Mean value:	263.047	Mean value mu:	263.047
Standard deviation:	30.1132	Standard deviation s:	30.1132
Limit : Failure Limit			
	Lower value = not set	Upper value = 300	Total
P_rel:		0.13	0.13
P_fit:		0.109887	0.109887
Sigma-Level:		1.22713	

Figure 5.5: Result of initial robustness evaluation of lug

The initial robustness evaluation aimed to assess the nominal design's robustness under various uncertainties, including material properties, applied loads and geometric dimensions. This evaluation considered 18 input parameters, which were varied using the Advanced Latin Hypercube Sampling technique. The resulting histogram is shown in Figure 5.5. The probability of failure was observed to be 13% when the stress threshold limit was set at 300 MPa, with a corresponding sigma level of only 1.227. This relatively low sigma value clearly indicates that the nominal design is inadequate in terms of structural reliability. For critical engineering components such as the lug, a desired sigma level is 4.5.

The COP matrix from the robustness analysis, which is typically used to evaluate the parameter's relative influence on the response, did not yield significant insights in this case. This was primarily due to the dominance of the externally applied tensile load in driving the maximum equivalent stress, which overshadowed the effects of other input parameters. As a result, the diagnostic value of the COP matrix was limited. Nonetheless, this outcome establishes the requirement for further rigorous design optimization to enhance the robustness of the design.

5.2.3 Sensitivity analysis

To gain deeper insight into which parameters most significantly influenced the responses of geometric mass and maximum equivalent stress, a detailed sensitivity analysis was conducted. The results of the initial sensitivity analysis indicated that achieving the desired maximum equivalent stress levels was not feasible within the bounds of the current design space. However, despite this particular limitation, the sensitivity analysis still serves as a fair assessment of the degree of influence of the parameters on the responses. This assessment serves as a foundational step toward guiding design modifications.

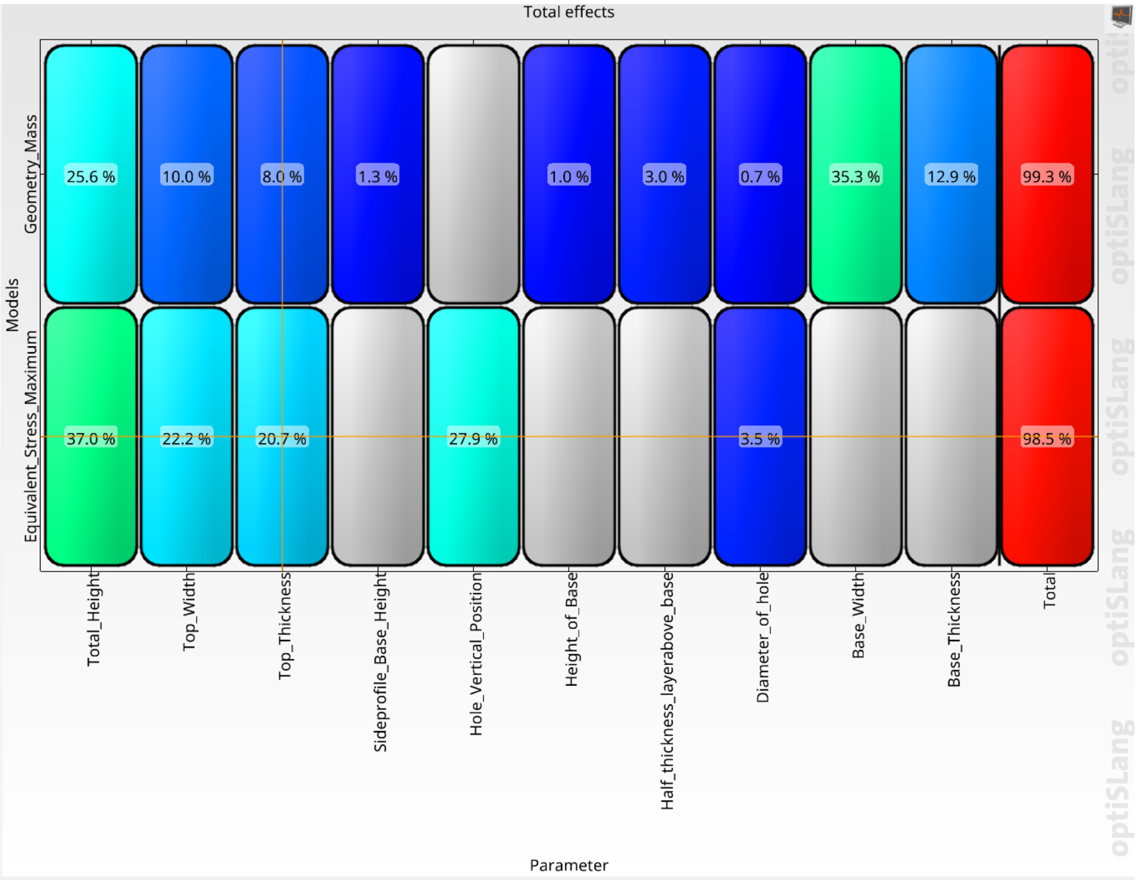


Figure 5.6: Result of initial Sensitivity analysis COP matrix

The insights study of COP matrix illustrated in figure 5.6 from the sensitivity analysis are noted below:

- The Total Height was identified as the most influential parameter affecting the maximum equivalent stress response. Additionally, Top Width, Top Thickness and Hole Vertical Position exhibited similar degrees of influence on maximum equivalent stress, displaying nonlinear trends within the considered parameter ranges. While these factors also contributed to the geometric mass, their impact on mass was comparatively smaller. Notably, the Hole Vertical Position had a significant effect on maximum equivalent stress but showed no measurable contribution to the geometric mass.

- The geometric mass is primarily influenced by Base Width and Total Height, exhibiting a linear relationship, followed by Base Thickness and Top Width which have a secondary impact.

- The parameters Sideprofile Base Height, Height of Base, Half Thickness Layer Above Base, Base Width and Base Thickness influence the geometric mass but do not affect the maximum equivalent stress. Therefore, these parameters can be strategically kept to the minimum in the interest of minimizing the mass without compromising stress performance.

- To capture design points with lower stress values, the range of the most influential factors on stress,namely Total Height, Top Width, Top Thickness and Hole Vertical Position were increased.

- The user defined constraints, such as a constant base thickness and stricter limits on hole diameter, are imposed. The specified requirement for Hole Vertical Position is ensured through appropriate selection of the design space. Prioritizing parameters based on sensitivity analysis is a crucial step to adjust the design space, improve computational efficiency and set the foundation for effective optimization.

The parameter values listed in Table C.3 from the sensitivity analysis correspond to the minimum mass design that meets the stress criteria of 198.281 MPa. These design points serve as the starting point for the optimization cycle I.

5.2.4 Design optimization

First robust design optimization criteria

$$\text{Mean stress} + 4.5 \times \text{Mean stress} \times \text{CoV} \leq 300$$

$$\text{Mean stress} \leq 198.281 \text{ MPa}$$

The sensitivity analysis results helped prioritize the geometric parameters namely Total Height, Top Width, Top Thickness, and Hole Vertical Position while simplifying the analysis and providing insight into parameters that could be kept constant. The modified ranges and further changes are specified in Figure C.9.

After evaluating 200 design points, it was observed that the best design 153, achieved a maximum equivalent stress of 198.18 MPa and a geometric mass of 0.201 kg (see

Figures C.10 and C.11). The corresponding values of the critical parameters are listed in Table C.4.

The robustness evaluation yielded a sigma value of 2.62 with a failure probability of 0.01 (see Figure C.12). While this represents an improvement over the nominal design, the current design is still considered non-robust since it falls short of the target sigma level of 4.5. Reliability analysis was also conducted to tabulate and better understand these values.

These results indicate that stricter criteria should be adopted to meet the 4.5 sigma requirement. It is also possible to estimate new criteria through extrapolation based on a linear assumption between the reliability index and mean stress. However, to ensure a thorough exploration of the design space, this approach will be employed only if robustness is not achieved under the stricter criteria.

Second robust design optimization criteria

Since the 4 sigma criteria did not yield satisfactory results, a stricter criteria of 6 sigma was considered. The resulting expression is provided below:

$$\text{Mean stress} + 6 \times \text{Mean stress} \times \text{CoV} \leq 300$$

$$\text{Mean stress} \leq 164.523 \text{ MPa}$$

After evaluating 200 design points, the best design identified was design 142. This design achieved maximum stress of 164.523 MPa and a geometric mass of 0.2126 kg (refer to figure C.15). The corresponding parameter values are summarized in table C.5.

The robustness evaluation yields a sigma value of 4.9 with a failure probability of 10^{-7} (see figure C.16). At first glance, the design can be considered robust since it meets and exceeds the required threshold of 4.5 sigma. This assessment holds true when the 300 MPa limit is treated as a fixed deterministic constraint. However, when the limit is modeled as a probabilistic distribution, the sigma value is expected to decrease, indicating a higher failure probability. To verify this, a reliability analysis was conducted considering the limit as a probability distribution.

Under the reliability analysis (figure C.17), the failure probability increases from 10^{-7} to 10^{-5} with a corresponding reliability index of 3.3. This result indicates that when uncertainties in both the design parameters and the limit state function are considered, the current design fails more frequently than the allowable threshold. To meet the robustness criteria of at least 4.5 sigma, the design's failure probability should be less than 10^{-6}.

5.2.5 Final design optimization

The criteria used in the previous optimization cycle resulted in a failure probability close to the target value of 10^{-6}. This suggests that the optimal design could be achieved by adopting criteria near the previous stress value. To quantify the value, a linear interpolation with the observed reliability index and mean stress was conducted. This value falls around the mean stress value of 150 MPa.

5.2.5.1 Design optimization

The best design after evaluating 200 design points was identified as design 81, with the corresponding parameter values summarized in Table C.6.

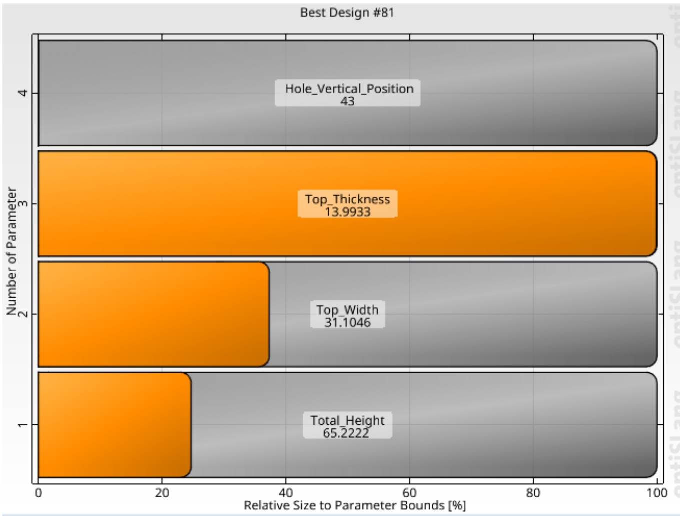


Figure 5.7: Values of parameters from optimization III

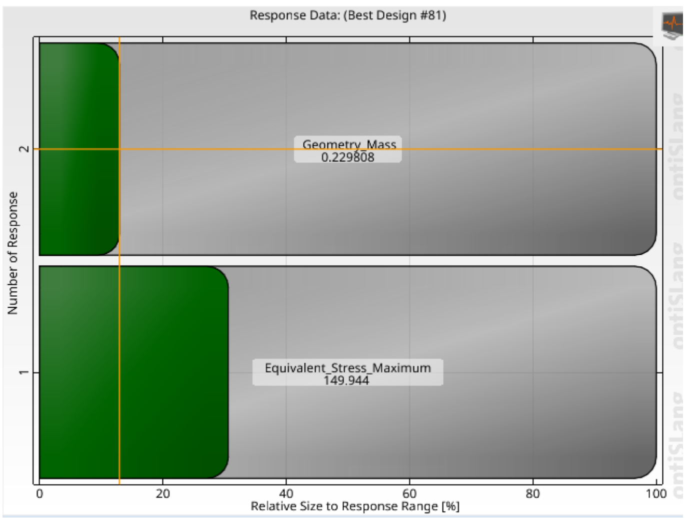
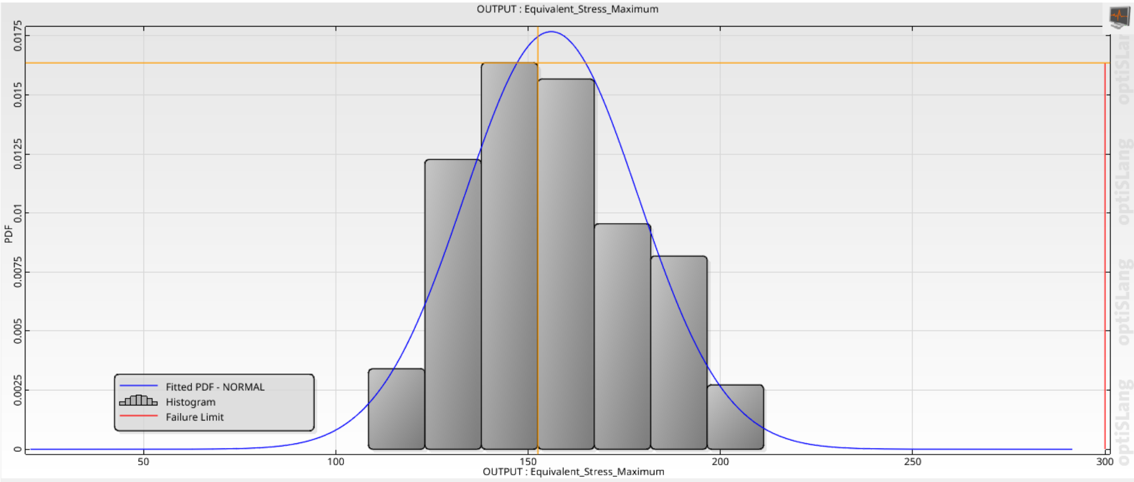


Figure 5.8: Values of responses from optimization III

5.2.5.2 Robustness evaluation and reliability analysis

From Figure 5.9, the robustness evaluation yields a sigma value of 6.37 with a failure probability of 10^{-11}. These values significantly exceed the required thresholds, strongly indicating that this design could be the optimal robust solution. To further validate the sigma level, a reliability analysis considering the limit as a probability distribution was also conducted. As illustrated in Figure 5.10, the reliability index is 4.4 with a corresponding failure probability of 10^{-6}.



Hide Statistical data

Statistical data			
Min:	108.494	Max:	211.228
Mean value:	156.029	Standard deviation:	22.571
CoV:	0.144659		
Skewness:	0.216084	Excess kurtosis:	-0.526112
Fitted PDF : NORMAL			
Statistical Moments		Parameter	
Mean value:	156.029	Mean value mu:	156.029
Standard deviation:	22.571	Standard deviation s:	22.571
Limit : Failure Limit			
	Lower value = not set	Upper value = 300	Total
P_rel:		0	0
P_fit:		8.93789e-11	8.93789e-11
Sigma-Level:		6.37856	

Figure 5.9: Result of robustness analysis III

Method : Adaptive Response Surface Method (ARSM)

Complete approximations : 3 / 3
Selected data : 3. Approximation

Probability of Failure : 5.31808e-06
Standard deviation error : 1.09673e-06
Reliability Index : 4.40382

Approximation errors : R^2 / R^2pred
lim_st_Equivalent_Stress_Maximum: 1 / 0.067833

Figure 5.10: Result of reliability analysis III

This design surpassed all robustness and reliability benchmarks. The consistently low failure probabilities under both fixed and probabilistic limit conditions demonstrate a highly reliable and structurally efficient solution, effectively marking the successful conclusion of the OptiSLang-based iterative optimization process.

5.3 Probabilistic analysis of lug using Probabilistic VMEA and OptiSLang

To explore a more simplified approach to robustness optimization, a parallel study was conducted using the Probabilistic VMEA method. Based on the sensitivity analysis, a subset of critical parameters was selected and varied within a narrowed design space. A full factorial design of experiments (DOE) was employed to systematically evaluate all parameter combinations.

The significant parameters were varied at the extreme values of this new design space. The new design space is obtained by reducing 1 sigma from the extremes of the initial design space. The specific parameter values considered for the DOE are tabulated in Table 5.1.

Ranges and average values of parameters			
Parameter	**Min**	**Average**	**Max**
Youngs modulus	**1,90E+11**	2,00E+11	**2,10E+11**
Poisson	**0,285**	0,3	**0,315**
Force Y	**8400**	9000	**9600**
Density		7850	
Base_Width	44	49,5	55
Sideprofile_Base_Height	8	11	14
sideprofile_ chamfer_angle	63	70	77
Half_thickness_layerabove_base	5,4	6	6,6
sideprofile_topfillet_rad	9	10	11
Base_Thickness		**20**	
Height_of_Base	15,3	17	18,7
Large_Fillet_Radius	9	10	11
Middle_Angle	40,5	45	49,5
Diameter_of_hole	16	16,009	16,018
Total_height	63	67,5	72
Top_Thickness	7	10,5	14
Hole_Vertical_Position	43	47	51
Top_Width	27	32,5	38
RESTRICTING 1 SIGMA FROM BOTH END TOWARDS THE MEAN			
Adjusted Range			
Total_height	**64,5**		**70,5**
Top_Thickness	**8,166**		**12,834**
Hole_Vertical_Position	**44,333**		**49,667**
Top_Width	**28,833**		**36,167**

Table 5.1: Constrained design space for full factorial DOE

Probabilistic VMEA table

The resulting value of 149.358 MPa from the Probabilistic VMEA (Table 5.2) is considered as the optimization criterion.

Parameter	Effect	Type of parameter	Min	Max	Max strength	Min strength		Log(max)	Log(min)	Delta
Force_Y_Component	Yes	Load	8400	9600	236,36	206,82		5,4654	5,3318	0,0223
Young's_Modulus	No	Material	1,90E+11	2,10E+11	221,59	221,59		5,4008	5,4008	0,0000
Total_height	Yes	Geometric	64,5	70,5	230,48	212,69		5,4402	5,3598	0,0134
Poisson's_Ratio	No	Material	0,285	0,315	221,81	221,37		5,4018	5,3998	0,0003
Top_Thickness	Yes	Geometric	8,166	12,834	271,38	171,80		5,6035	5,1463	0,0762
Hole_Vertical_Position	Yes	Geometric	44,333	49,667	231,96	211,21		5,4466	5,3529	0,0156
Top_Width	Yes	Geometric	28,833	36,167	242,12	201,06		5,4894	5,3036	0,0310
									Total	0,0877
						Average Equivalent Stress	221,59	5,4008		1,4836
								0,3945		
								5,0064	149,3588	

Table 5.2: Probabilistic VMEA calculation of lug

5.3.1 Optimization using probabilistic VMEA

The value obtained as the result of Probabilistic VMEA is used as the optimization criteria. The sequence of steps involved in the novel workflow is illustrated in Figure 5.11.

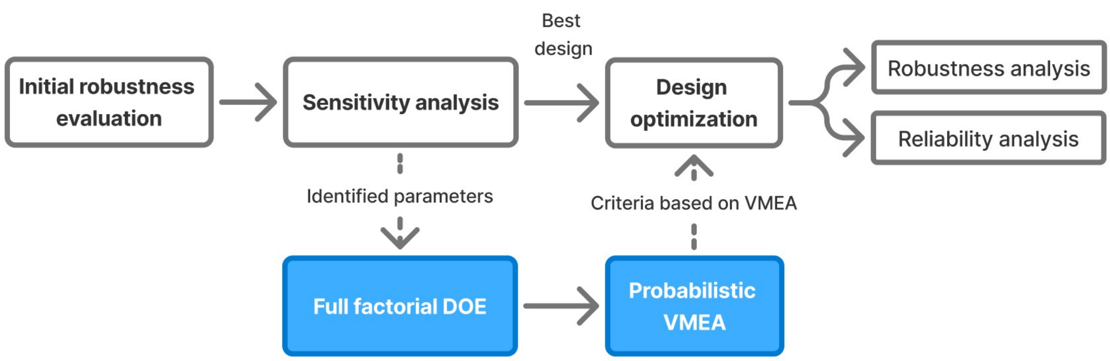


Figure 5.11: Probabilistic VMEA workflow of lug

The best design, identified after evaluating 200 design points is design 195. The corresponding parameter values are tabulated in Table 5.3.

Table 5.3: Best design : Probabilistic VMEA Optimization

Parameter name	Parameter value
Base_Thickness	20
Base_Width	44
Density	7850
Diameter_of_hole	16.009
Force_Y_Component	9000
Half_thickness_layerabove_base	5.4
Height_of_Base	15.3
Hole_Vertical_Position	43.07
Large_Fillet_Radius	10
Middle_Angle	45
Poisson's_Ratio	0.3
Sideprofile_Base_Height	8
Sideprofile_topfillet_rad	10
Top_Thickness	13.925
Top_Width	32.268
Total_Height	63.244
Young's_Modulus	2,00E+11
sideprofile_chamfer_angle	70
Equivalent_Stress_Maximum	148.341
Geometry_Mass	0.2277

5.3.2 Robustness evaluation and reliability analysis

The optimization using the criteria obtained through the Probabilistic VMEA method was initially hypothesized to produce an optimal design meeting the specified requirements in a single optimization cycle. From figure C.18, the robustness evaluation based on this criteria yielded a sigma value of 6.4, which significantly exceeds the requirement. This strongly indicates that the resulting design could be considered optimally robust. To verify this sigma level, a reliability analysis was also conducted.

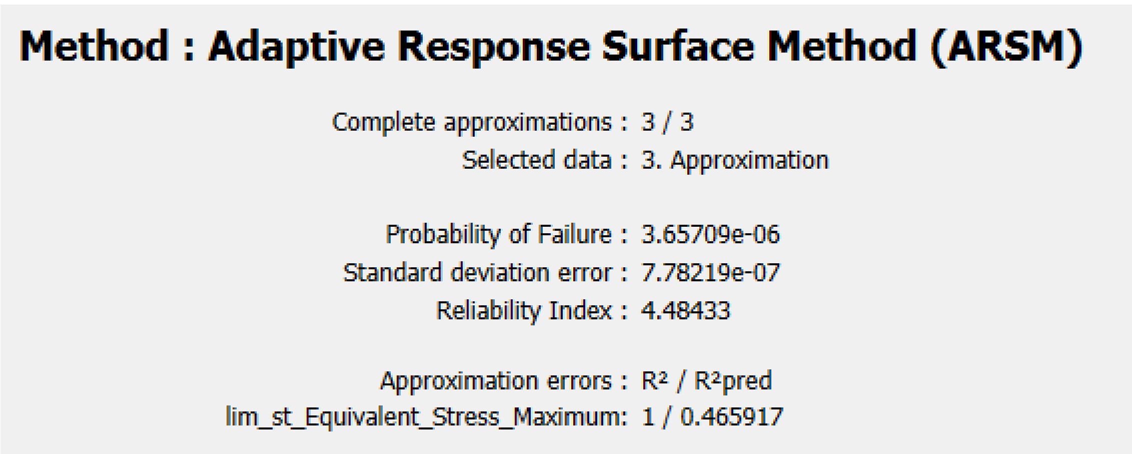


Figure 5.12: Result of reliability analysis with probabilistic VMEA workflow

From figure 5.12, the reliability analysis of the current best design yielded a reliability index of 4.48 and a failure probability of 10^{-6}.

5.4 Reflections on the conventional approach and Probabilistic VMEA integrated approaches

To identify the most efficient robustness optimization methodology, two approaches were explored: a multi-cycle iterative process using OptiSLang, and a single-cycle optimization combining OptiSLang with probabilistic VMEA.

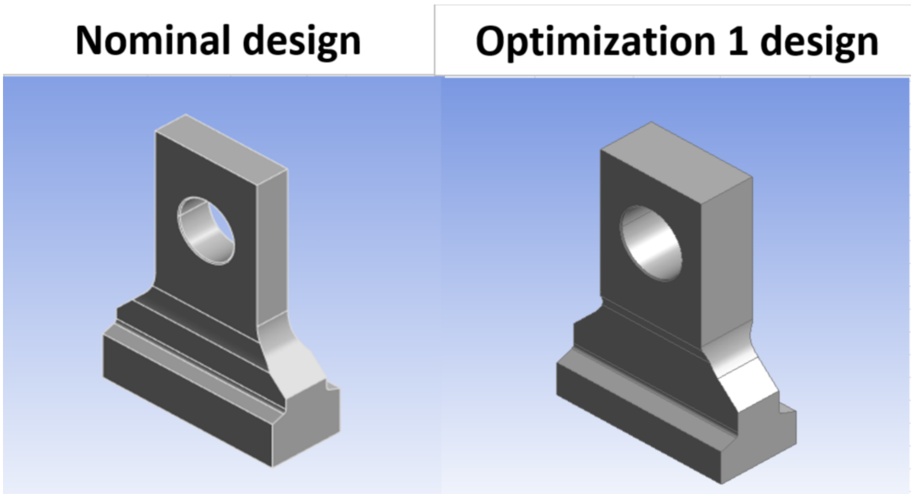


Figure 5.13: The nominal geometry and geometry from first optimization cycle

Judging from Table 5.4, the current workflow converts the nominal design that is initially non-robust, as shown in Figure 5.13. The robustness is only achieved through further refinements. Moreover, an initial visual comparison of the robust geometries from both approaches (Figure 5.14) reveals that the optimized solutions are very similar.

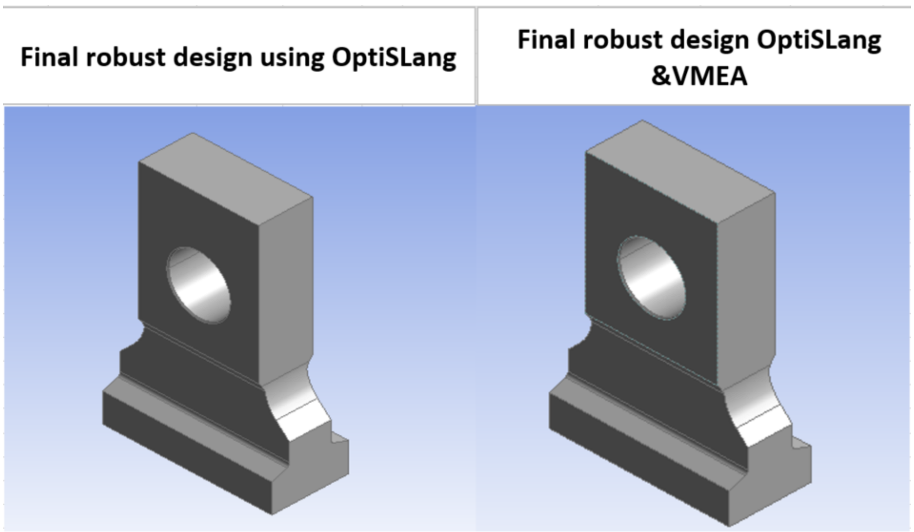


Figure 5.14: The Robust design from OptiSLang robustness optimization and the robust design from the integrated workflow

Parameter	Type	Nominal	Design 1	Design 2	Design 3	VMEA	Unit
Input	Total_height	70	63	63,06	65,22	65,22	mm
	Top_Thickness	9	13,55	13,89	13,99	13,99	mm
	Hole_Vertical_Position	50	46,58	43,33	43	43	mm
	Top_Width	30	27	29,04	31,10	31,10	mm
	Density	7850	7850	7850	7850	7850	mm
	Base_Width	50	44	44	44	44	mm
	Sideprofile_Base_Height	12	8	8	8	8	mm
	sideprofile_chamfer_angle	70	70	70	70	70	degree
	Half_thickness_layerabove_base	6	5,4	5,4	5,4	5,4	mm
	sideprofile_topfillet_rad	10	10	10	10	10	mm
	Base_Thickness	20	20	20	20	20	mm
	Height_of_Base	17	15,3	15,3	15,3	15,3	mm
	Large_Fillet_Radius	10	10	10	10	10	mm
	Middle_Angle	45	45	45	45	45	degree
	Diameter_of_hole	16	16,009	16,009	16,009	16,009	mm
	Factors	Nominal	Design 1	Design 2	Design 3	VMEA	
Output	Geometric mass	0,2321	0,2015	0,2126	0,2298	0,2277	Kg
	Equivalent stress	263,55	198,188	164,523	149,994	148,341	Mpa
	Reliability index	1,23	2,04	3,30	4,40	4,48	Dimensionless
	Faliure probability	13%	0,0207	4,83E-04	5,32E-06	3,67E-06	Percentage

Table 5.4: Comparison of all designs

A closer inspection of Table 5.4 indicates that both methods produced designs with comparable robustness and minimal mass. The final iteration of the OptiSLang-based approach achieved a maximum equivalent stress of 149.994 MPa and a geometric mass of 0.2298 kg. Meanwhile, the probabilistic VMEA-based design slightly outperformed this by reducing stress to 148.341 MPa and achieving a marginally lighter mass of 0.2277 kg. Although these differences are small, the probabilistic VMEA approach demonstrates a slightly better balance between stress reduction and material usage.

Criteria	Maximum equivalent stress (MPa)	Geometry mass (kg)	Achieved sigma level robustness-analysis	Failure probability reliability analysis	Reliability index
OptiSlang method	149,94	0,2298	6,37	5,3E-06	4,4
VMEA-based method	148,34	0,2277	6,4	3,67E-06	4,48

Table 5.5: Comparison of results

From the comparison of the results in Table 5.5, the OptiSLang approach achieved a robustness sigma level of 6.37 with a failure probability of 10^{-11} after three optimization cycles and successive robustness evaluations. However, reliability analysis tuning indicated a higher failure probability of 5.32×10^{-6} and a corresponding reliability index of 4.4.

The probabilistic VMEA approach achieved a comparable sigma level of 6.48 and a failure probability of 10^{-11} in a single optimization cycle. Subsequent reliability analysis refinement resulted in a slightly improved reliability index of 4.48, with an arguably lower failure probability of 3.67×10^{-6}.

Criteria	Number of sensitivity analyses	Number of optimization cycles	Number of robustness evaluation	Number of reliability analyses	Full factorial design of experiments (DOE)
OptiSlang method	2	3	4	3 (1 optional)	Nil
VMEA-based method	2	1	2	1	1 (reduced design space)

Table 5.6: Workflow Comparison: Number of Steps

While both approaches met or exceeded the required 4.5 sigma threshold for critical structural robustness, the probabilistic VMEA-based method demonstrated a more streamlined path to achieving these results, as illustrated in Table 5.6. The most significant differentiator between the two lies in computational time and resource efficiency. As evident from Table 5.7, the probabilistic VMEA approach required fewer steps and yielded a substantial reduction in the time needed for robustness optimization.

Criteria	Total time for sensitivity analysis	Total time for optimization cycles	Total time for robustness evaluation	Total time for reliability analysis	Full Factorial DOE Time	Total computational time
OptiSlang method	1 hr* 2 (300 samples) = 2 hrs	3 hrs 30 mins * 3 (200 samples) = 10 hrs 30 mins	1 hr 30 mins *4(100 samples) = 6 hrs	6 hrs * 3(330 samples) = 18 hrs	Nil	**36,5 hrs *(25,5 hrs if the first optimization cycle is skipped)**
VMEA-based method	1 hr * 2(300 samples) = 2 hrs	3 hrs 30 mins *1 (200 samples)= 3 hrs 30 mins	1 hr 30 mins *2(100 samples) = 3 hrs	6 hrs *1(330 samples)= 6 hrs	1 hr 30 mins *1 (128 samples) = 1 hr 30 min	**14 hrs**

Table 5.7: Workflow Comparison: Computational time

As observed, the probabilistic VMEA integrated approach required less than 60% of the computational time compared to the conventional OptiSLang method, indicating a more direct and efficient path to convergence toward a robust solution. This marked improvement in efficiency makes the new method particularly attractive for projects constrained by tight timelines or limited computational resources, positioning it as a compelling option for agile product development environments.

On the other hand, the OptiSLang approach is well suited for deep sequential exploration, offering valuable insights into variable dependencies and design trends. Due to its iterative nature, it is more resource-intensive but allows for greater flexibility and adaptability, especially when mid-course corrections are required. While the faster, probabilistic VMEA approach achieved comparable results in this study, the number of parameters considered for the full factorial DOE can be a significant choke point. Additionally, since the probabilistic VMEA method involves only a single optimization cycle, there is a possibility that it could lead to a conservative design when faced with conflicting objectives such as minimizing both mass and maximum equivalent stress. Although this limitation was not observed in the current study, it remains a relevant consideration for broader applicability.

5.5 Conclusion

The computational study using ANSYS OptiSLang facilitated the integration of variation-based robustness and reliability analysis into the design optimization process. Notably, the constraint criteria for the optimization, such as maximum equivalent stress in this case, can be defined using multiple approaches. These varying approaches were explored and critically evaluated within the study. The insights gained reflect the robustness and soundness of the methods used to define the constraint criteria that guide the optimization process, as detailed below::

1. **Derivation of criteria from mathematical relation:**

   $$\text{New criteria} + \text{Desired sigma level} \times \text{New criteria} \times \text{CoV} \leq \text{Threshold value}$$

   This approach is mathematically sound and offers greater transparency. It allows for straightforward adaptation of stricter sigma levels if the initial criteria do not produce a robust and reliable design. The simplicity in criteria derivation and transparency of the method comes under the cost of computational resources. As observed in the computational study, this approach requires multiple optimization cycles, each of which can be time-intensive, resulting in longer total computation times.

2. **Criteria based on mean stress and failure probability:** Interpolating the mean stress value based on observed failure probabilities inherently assumes a linear relationship between mean stress and reliability index. During the computational study, it was observed that relying on this linear interpolation approach produced unreliable results when assessed against engineering judgment.

3. **Criteria from mean stress and reliability Index:** This approach, which involves estimating the design criteria through linear interpolation between mean stress and the corresponding reliability index, was found to be mathematically sound and bears satisfactory results in the computational study. This makes it a viable option for guiding robustness-focused optimization with a key limitation that it requires at least one complete optimization cycle to generate the data needed for interpolation. As a result, achieving and verifying a robust design typically demands two optimization cycles, increasing the overall computational effort and time.

4. **Probabilistic VMEA approach:** The novel approach of probabilistic VMEA in deriving the criteria resulted in a similar design as the conventional mathematical approaches with the prerequisite of only sensitivity result to prioritize the parameters for full factorial DOE. The key advantage of this method lies in its streamlined workflow, achieving a robust and reliable design through a single optimization and verification cycle.

From a structural robustness standpoint, the computational study highlighted that achieving robustness does not necessarily equate to adding more material but rather optimizing material distribution strategically relocating it to regions where load handling is most critical.

What this revealed is that robustness can no longer be treated as a passive outcome it must be a design target. The platform of ANSYS OptiSLang provides a workable structure for embedding robustness analysis early in the design process. The limitations of the existing workflow were also exposed as both the models were evaluated as non-robust if stochastic variations which are more representative models of real-life situations were considered. Through iterations, driven by robustness-based criteria, both models were optimized into designs that met the 4.5 sigma threshold. The probabilistic VMEA methodology significantly reduced the number of cycles and time needed to reach an optimal result.

6

Conclusion

6.1 Conclusion

In the final chapter, the two research questions that structured the investigation are revisited to produce a clear conclusion rooted in insight revealed during the thesis work. The exploration of design margins through the lens of both qualitative insight and qualitative validation revealed that the challenges are deeply intertwined, each building one another. To understand the challenges around design margins a broader exploration was conducted on robustness and uncertainty since margins are a response to uncertainty to safeguard robustness and performance. The detailed conclusions in each section have been drawn and a brief combined reflection on these topics helps to craft a unique overview of the research questions.

RQ1: What are the current industrial challenges related to the design processes in regards to the use of design margins?

The qualitative study revealed that while organizations aim to push the boundaries of performance with safety as a priority, the increasing complexity and the uncertainties involved in the real world act as a counterforce. These uncertainties stem primarily from unclear customer inputs, emerging technologies and evolving load conditions.

It is observed that the risks posed by known uncertainties are quantified and absorbed using margins from design practices. The way margins are currently handled in practice revealed both technical and cultural patterns. They are treated as inherited defaults which are handed down from historic data from successful projects and practices. Eventually, the justification behind the marginal derivation becomes fogged and disconnected from the evolving reality. This results in the paradigm where the margin stops acting as a precision tool but is like an unquestionable instrument.

From the study, it became evident that industrial practices around design margins are shaped by cautious grounded conservatism. Engineers rely heavily on past data, not necessarily out of preference, but to satisfy regulatory demands that favor familiarity. This stiffness affects any marginal management initiatives. Known uncertainties are largely absorbed into numerous and broader margins reflecting further on the industrial conservatism. This marginal consideration can intensify performance tradeoffs.

Additionally, the robustness itself is interpreted differently and uncertainties faced at different stages and functions are also diverse. This situation can result in multiple design margins compensating for the same certainties at different stages as the communications between the fields become limited.

Drawing from these observations, the challenge with design margins is not that they exist but rather how they are handled as passive safety. The current industrial process does not always enable teams to trace the reasoning, evaluate or evolve margins with respect to the product's evolving uncertainty profile.

RQ2: What is the process of working with design margins and robustness at GKN and how can it be improved?

The RQ2 was addressed through a blend of qualitative insights followed by computational study in ANSYS OptiSLang. The aim was not limited to understanding how margins are applied but rather also to investigate whether computationally based strategies could improve the robustness of the design.

At GKN, the process of working with design margins is grounded in experience guided by legacy rules in design practices and certification standards, revised only if performance anomalies demand the change.

From the qualitative study, it was understood that the factor of robust design although often spoken about, but rarely addressed in a structured way at the early stages of phases of design. The robustness is rather passively achieved as a by-product of adhering to design margins and established practices. The design margins are introduced in all stages and little to no evidence was found whether the marginal considerations are actively managed to prevent over-design.

It was noticed that OptiSLang is limitedly used at GKN, mainly restricted to design optimization tasks. The full potential of the tool for robustness evaluation and reliability analysis remains untapped. This underutilization presents a critical opportunity which was exploited in the computational study conducted in the thesis.

The computational study in this thesis verified the potential of OptiSLang not just as a design optimization tool, but also as a platform to integrate robustness and uncertainty. Furthermore, the platform also provides flexibility to incorporate multiple objectives and offers an opportunity for better handling of trade-offs. Each functional team has its own internal definition of what should be achieved in that stage and what robustness means in that specific aspect. This ability to unify different functional perspectives within a single analysis framework enhances transparency and promotes system-level decision-making.

The steel hook and lug models served as powerful proof of concept cases for the inclusion of robustness evaluation, as well as the new workflow using probabilistic

VMEA. The integrated probabilistic VMEA workflow that was conducted on both the hook and lug geometries demonstrated promising potential in identifying robust and lightweight solutions efficiently in reduced computational time.

The setting of robustness targets like defining stress thresholds based on sigma levels can itself be seen as a form of design margin. Both lug and hook analysis indicated that achieving robustness requires a mean stress margin of approximately 0.5 times the stress limit. Although this observation is preliminary, it provides a compelling basis for further investigation.

These early findings suggest that this approach could offer significant value to the organization by enabling more informed design decisions with reduced computational effort and improved robustness assurance.

Therefore, the answer to RQ2 is not just procedural but it is also philosophical. The current process at GKN reflects a legacy mindset that assumes robustness will happen if past practices are followed. Many engineers are trained to design for a fixed limit, not to understand the probability of failure around it. The improved process tested in the thesis shows that robustness can be better handled by actively designed and tools like OptiSLang. It enables teams to not just optimize and embed reliability into the geometry but rather serve as a platform for collective analyses of objectives from multiple functional areas which improves the clarity in the trade-off made.

6.1.1 Recommendations

The insights from this thesis are not intended to critique the current process rather consider these as suggestions meant to support continuous improvements, leverage opportunities and aid the evolution of processes. Both the qualitative and quantitative studies highlighted areas where existing methods can be refined and extended. Based on insight from the thesis work, the following recommendations are suggested for future work and implementation:

Improve traceability and access to historical data.

Investing in better tools to retrieve and interpret historical margin decisions and reasoning in deriving them and designing trade-offs would help reduce redundancy and increase the quality of future decisions.

Cultivate a shared vocabulary and philosophy across disciplines.

As an initial step to enable communication between functional areas, a shared vocabulary of terms with multiple definitions is suggested. This will extend the understanding of challenges faced by different functional areas.

Investigations into marginal management.

The computational analysis was suggestive of 0.5 as a marginal factor for robustness within the limits of parameters considered. Further investigations could be conducted to ensure the margins considered at different stages don't stake up and result in overdesign.

Build internal capability and comfort with probabilistic design thinking.

A recurring observation during the reflection on the AIM diagram in probabilistic design in Figure refAIM diagram on probabilistic design was that these are very limitedly used and many engineers are unaware of the potential of probabilistic tools and approaches. There should be a shift from a deterministic mindset. Investing in training programs and internal knowledge around probabilistic design could help close this gap and build a more robust decision-making culture.

Expand the role of OptiSLang beyond optimization.

The computational study showed that the platform of OptiSLang is capable of more than just helping find optimal geometries. It brought much-needed structure and insight into how robustness and reliability are approached in the thesis. GKN should consider integrating robustness analysis and probabilistic VMEA into its standard workflow, enabling it to assess deeper assessment of confidence in design performance.

Pilot probabilistic workflows.

While the hook and lug models served as controlled environments for proof of concept testing, the next step would be to trial this robustness workflow on an actual product in the development of a noncritical component for understanding further feasibility and learning..

6.1.2 Additional recommendations for investigation on the integrated workflow.

1. Study of probabilistic VMEA workflow in nonlinear static structural behavior.

   In the thesis, the study explored the effectiveness of probabilistic VMEA under the consideration of the linear behavior of the model. It is highly recommended to explore the same methodology for nonlinear static structural analysis.

2. Investigation of probabilistic VMEA workflow under conflicting objectives and different load conditions.

   The current exploration was confined to responses of mass and maximum equivalent stress. The same methodology must be tested under different load conditions such as thermal and aerodynamic load, fatigue effect, etc for further validation of its effectiveness. The conflicting objective can give rise to trade-offs, as robustness in one aspect doesn't guarantee the same level of immunity towards variations on other types of loads. The current method should be required to develop further to incorporate these trade-off factors to produce a well-adaptive criteria for optimization. The computational time benefits and its comparisons based on the new conditions also must be reevaluated.

3. Investigation into whether the single optimization approach aids conservatism of safety. The developed methodology provides benefits in computational time with the possible trade-off of resolution. Due to the single-step nature of the methodology, the question of whether the approach results in a conservative design is relevant. More investigation must be done to ensure there is no other optimal design point beyond the scope of the criteria obtained from probabilistic VMEA.

4. Investigation under different material selection.

   The current study considered structural steel as the material of the model and replicability of the observed trends should be verified with different materials. The situation can become more complex when multiple body interactions with different materials are included in the simulation model.

5. Investigation to enhance transparency in criteria derivation of Probabilistic VMEA.

   The method is inherently nonintuitive in its mathematical reasoning. It's unclear whether the criteria producing better results are arrived at by virtue of the design space or the limit considered. If it's a total design space-dependent result, the methodology must be modified to include the limit sensitivity into the mathematical framework.

6. Reevaluation of criteria on reducing the design space.

   The full factorial DOE is conducted on a design space which is one sigma level reduced from the extremes of the initial design space. The reduction criteria were based on pragmatism, not on strict mathematical reasoning. More sound criteria based on engineering should be derived to reduce the design space for better flexibility.

7. Investigating the reliability of the quality of meta-model of prognosis and usability of cop matrix in case of uneven design space In the thesis.

   In the thesis, during the investigation of the lug model, the initial design space considered was not able to produce a robust design point. This resulted in an additional sensitivity analysis with a skewed range on the most contributing parameters. The effectiveness of the metamodel under this change has to be investigated in better resolution so that the metamodel can be further used in the workflow. As more range is considered for some parameters the reliability of the COP matrix can also be questionable. This scenario also further suggests a need for better handling of the design space as well.

8. Investigation of probabilistic VMEA under different sampling strategies.

The current methodology demands a full factorial DOE as the input for conducting the probabilistic VMEA. This sampling strategy of full factorial DOE can produce a bottleneck as the sampling size increases exponentially with a number of parameters considered. This sampling strategy imposes an inherent limitation in the inclusion of all the factors from different areas all at once. Hence different sampling strategies should be explored for increasing the scope of the methodology.

9. Automation of probabilistic VMEA process.

   The current handling of the sampled full factorial values is done manually in MS Excel sheets. This manual number crunching poses the potential risk of human errors due to the possibility of mismanagement and misinterpretation. It is possible within the capability of ANSYS ACT to create a plugin in the workflow that conducts the probabilistic VMEA calculations automatically and saves the efforts of manual calculation with better time and precision benefits.

10. Flexibility of aerospace models at extreme points.

    The reliability analysis will consider parameter values that are beyond the specified ranges, resulting in design points with invalid geometry. Since aerodynamic designs can be highly complex such variations considered for reliability evaluation can result in an unclosed sketch in the geometry. Rectification of those can be time-consuming without much benefit in return. The need for parameterization of the complex geometries also poses a barrier on top of the challenge that the model can be corrupted if the values of the parameter are changed at once rather than a sequential approach in alteration.

11. Further clarification into the positioning of topology optimization.

    Even though a semi-optimized design is a pre-requisite for finer robustness optimization. Since the specific criteria against which the topology optimization should be conducted is unknown, the initial topology optimization can be difficult. The stage at which the topology optimization should be included is reflected and reassessed.

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A

Appendix A

A.1 Interview questions

These following question were use to guide the interview process. These questions were used just as reference and were adapted to best suit the semi formal discussion.

A.1.1 Robust design and uncertainty

1. What would be your definition of robustness in your field of design in product development?
2. What factors do you think are important to make a robust product?
3. What are the main challenges in achieving robustness in your designs?
4. What types of uncertainties are most common in your area of work?
5. What are the uncertainties considered to make the design robust?
6. How do you deal with these different uncertainties in design?
7. Are we handling uncertainties in enough detail or should more be done?
8. **If not**: What tools or practices do you believe are missing in your current approach to addressing uncertainties?
9. Do you use DFMEA or FMECA for recognizing this uncertainty? Or is it a standard approach—Design Practice?
10. Does uncertainty from different functional areas or teams impact your work?
11. Are the uncertainties from different functional areas communicated systematically to you?
12. If yes, how? What is the current practice at GKN?
13. Does knowledge of these uncertainties (in different functional areas) aid in

achieving better robustness?

14. Do you feel the parameters identified as the uncertainties are good to make the product robust?
15. Do you think the current methods for identifying and addressing uncertainties are sufficient? If not, what areas need improvement?
16. What challenges do you face in defining a knowledge space and design space?
17. From your perspective how do you feel uncertainties can be handled in a lean and cost effective manner, do you have any reflections or comments on the above.

A.1.2 Design margins

1. Are you using margins in your work?
2. How do you define design margins in your work?
3. What margins are considered in your work in connection to failure modes or uncertainties?
4. How do you decide the level of margins to use in your designs?
5. Do you think existing margin guidelines are too conservative?
6. What do you think is the consequence of applying more than necessary margins in your field?
7. Are you aware / made aware of what factors these margins account for?
8. Are margins and their sources considered in the different functional areas all systematically communicated to your area (Robustness)?
9. How are they communicated?
10. Do these margins in different functional areas affect your area of design?
11. Are the margins considered in your area communicated to other areas?
12. Can you share thoughts or reflections on what might be the current industrial challenge(s) related to the design process for design margins in aerospace?
13. How confident are you in the quality of the data you receive as input parameters for performing margin calculations? Are they reliable and precise?

A.1.3 Probabilistic design

Note that TBLP -Reliability based life prediction, is the internal name used at GKN for probabilistic VMEA.

1. What type of probabilistic methods and software are you aware of?
2. Have you used any probabilistic method such as Monte Carlo?
3. Do you know OptiSlang as a platform for studying variation in calculations?
4. Have you been trained in or used TBLP (Probabilistic VMEA – official name)?
5. What is your opinion about using TBLP in the context of robust design and design margins?
6. Do you feel the need for the TBLP method to be implemented in your area of work?
7. Do you think an expert in the method is needed to perform the calculations?
8. Do you feel it's too resource-intensive and time-consuming?
9. In your area of work, do you think there is a knowledge deficit for engineers to understand the TBLP model?
10. Do you think the TBLP method could be applied to the current design process?
11. What challenges do you feel might be faced in integrating the TBLP method into the current design process?
12. By using the TBLP method, do you feel a thorough robustness evaluation of the component or system is achieved?
13. What are some of the variations you take into consideration when using the TBLP method?
14. Do you feel that implementation of the TBLP method could aid in achieving a high-quality product compared to conventional methods used by GKN?

B

Appendix B

B.1 Qualitiative study

B.1.1 Robust design

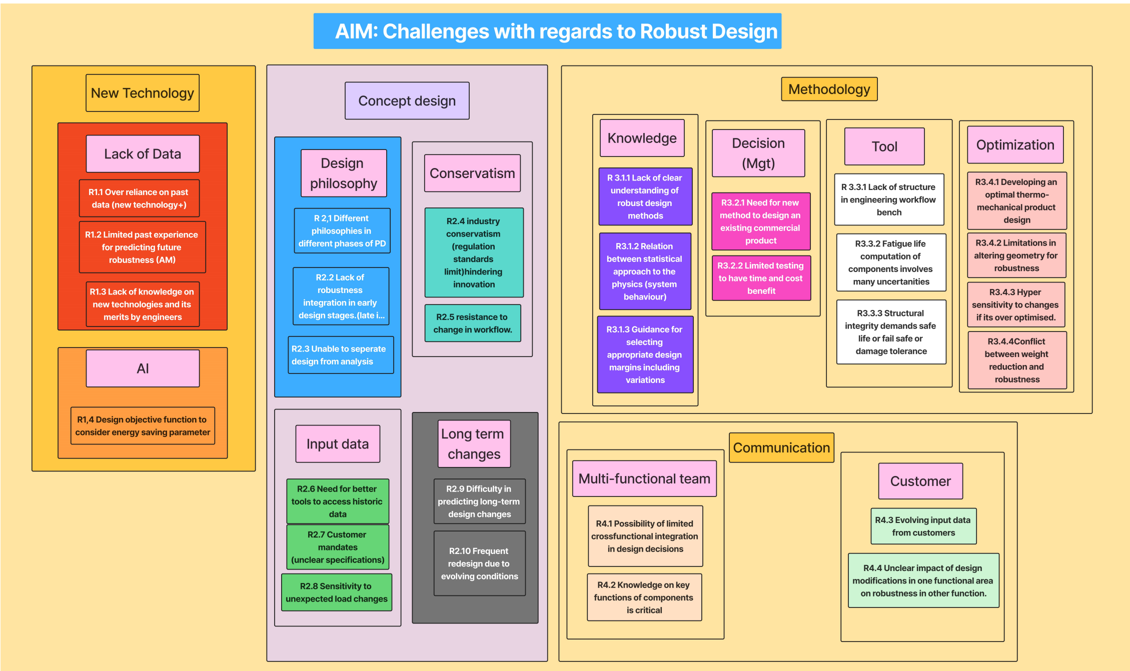


Figure B.1: Detailed AIM diagram of robust design

R2.4 Industry conservatism (regulation standards limit) hindering innovation.

This theme has emerged in all of the AIM diagrams, as there is across the board agreement that conservatism is prominent in aerospace industry. The heavy dependence on proven practices and the rigor of risk management required even for small changes affect the effective adoption of new methods and technologies in the industry. Practices such as assessment based on technology readiness levels enable risk aversion but at the cost of lowering the overall pace of technological advancement. This overall conservatism, coupled with the human tendency to maintain the status quo, contributes to the challenge of R2.5 resistance to change in workflow. The industry operates under strict time constraints, and any addition to the workflow demands substantial justification. It also raises the question of why a practice with a proven track record should be altered or even explored, especially when the new approach may lack such backing. This challenge makes explorations based on future visions harder to execute in the aerospace industry unless they can be supported by drastic and clearly tangible benefits.

R3.3.1 Lack of structure in engineering workflow bench.

The engineering workbench offers flexibility in the workflow at the compromise of clarity and direction. This paradigm of the workbench offers tremendous freedom for expert users to work with, while at the same time making it difficult for less experienced engineers to navigate.

R3.4.1 Developing an optimal thermo mechanical product design.

In the case of thermo mechanical models, the number of parameters considered can be high and the effect of optimization in one aspect of the design may not be intuitively understandable or clear in terms of its impact on others. This challenge is further explored and explained in the challenges of R4.4 unclear impact of design modification in one functional area on robustness in another functional area—and R3.4 conflict between weight reduction and robustness.

B.1.2 Uncertainty

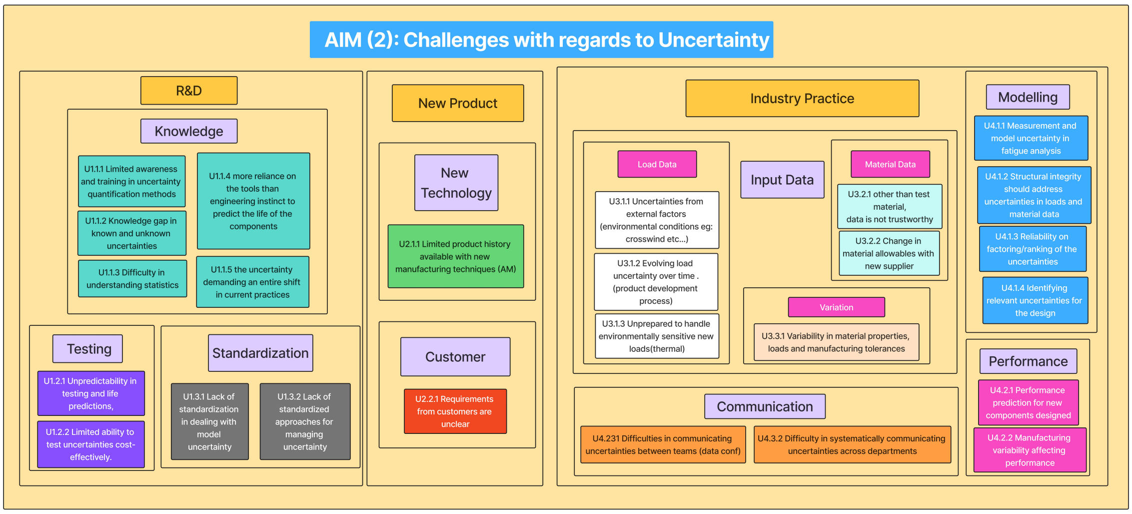


Figure B.2: Detailed AIM diagram of uncertainty

U1.3.2 Lack of standardized approaches for managing uncertainty

This challenge builds upon U1.3.1, as different uncertainty quantification methods are used even within the same organization. Leading companies often require probabilistic approaches to account for uncertainty, reflecting the importance of such analyses to high-stakes customers. However, while pioneers may implement probabilistic models, unless the entire value chain is aligned, these efforts remain isolated and fragmented. This limits the scalability and broader adoption of robust design methodologies and their validation. Additionally, the absence of standardized certification processes for aircraft parts based on probabilistic safety assessments rather than traditional deterministic margins, poses potential regulatory hurdles and uncertainties.

U3.1.1 Uncertainties from external factors (environmental conditions,crosswind)

The shear number of known uncertainties coupled with the nature of unknown uncertainties, poses significant prediction challenges. It is impractical to model all uncertainties within simulation frameworks factors such as sand ingestion or bird strikes are difficult to capture using traditional models. Ignoring these can lead to under designing components. This challenge should also be reflected upon when optimizing design margins. It is a valid consideration whether the unintended excess margins implicitly compensate for these unknown uncertainties.

U3.2.1 Other than test material, data is not trustworthy.

Material property tables in databases may not accurately represent the specific batch, supplier, or manufacturing process used. Additionally, as noted in U3.2.2, variations in material allowable values can occur when sourcing from different vendors due to subtle differences that often requiring re qualification.

U4.1.1 Measurement and model uncertainty in fatigue analysis.

Models are simplifications that often omit microdefects and surface roughness to streamline the analysis process. This lack of representation of such uncertainties can create a false sense of precision, introducing practical uncertainties regarding the effectiveness and reliability of the analysis.

U4.1.2 Structural integrity should address uncertainties in loads and material data.

Real world variations in load and material data cannot be effectively addressed using a static, single value approach, as it fails to represent expected operating conditions. Conversely, incorporating extensive variations through methods such as probabilistic analysis can significantly increase complexity, often without proportionate benefits in commercial aerospace applications. Since including more input variations typically leads to greater output variability, the key challenge lies in determining an optimal, affordable level of uncertainty to incorporate in the analysis.

Performance

U4.2.1 Performance prediction for new components designed.

Due to the lack of historical data, predicting the performance of new components is challenging. Consequently, uncertainties must be integrated into models from the outset. This challenge is closely related to the knowledge gap in both known and unknown uncertainties (U1.1.2) and the evolving nature of load uncertainties over time (U3.1.2).

U4.2.2 Manufacturing variability affecting performance.

The life difference between a rough machined part and a finely finished component exemplifies this challenge. Surface conditions significantly influence fatigue life and crack initiation while deviations in manufacturing can lead to unexpected failures. Since these effects cannot be accurately captured in models, overly conservative design margins are often necessary. Variability in final geometry is further affected by factors such as tool wear, process control, and operator skill. Additionally, residual stresses introduced during manufacturing processes, especially heat treatment, create further uncertainties in long term performance.

B.1.3 Design margins

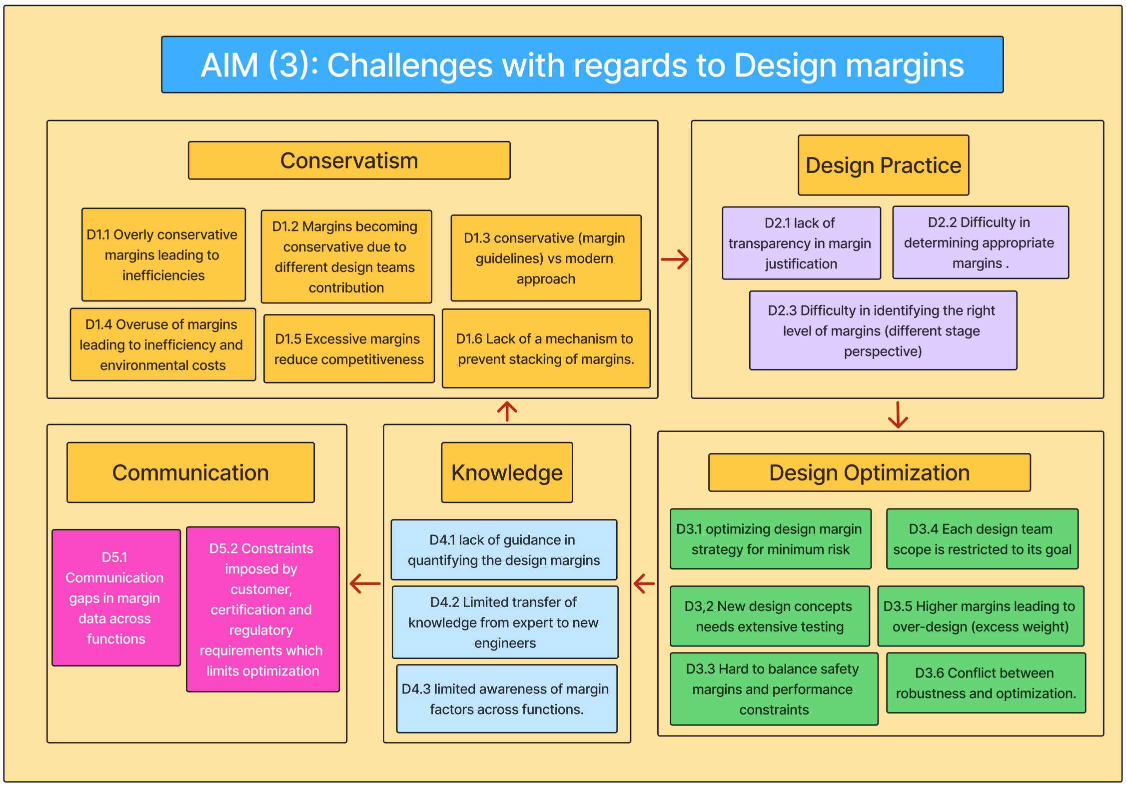


Figure B.3: Detailed AIM diagram of design margins

D1.4 Overuse of margins leading to inefficiency and environmental costs.

Building on challenge D1.1 overly conservative margins leading to inefficiencies, this issue carries significant sustainability implications. Excessive design margins not only cause material waste but also contribute to increased emissions throughout the product's life cycle due to higher fuel consumption from added weight. While these margins typically provide safety within an acceptable trade- ff between performance and environmental impact, the lack of a systematic method to prevent redundant or overlapping margins enhance inefficiencies. This is a widespread challenge in aerospace, highlighted here through the lens of growing awareness of the environmental consequences of such conservative design practices.

D1.5 Excessive margins reduce competitiveness

This challenge should be viewed as an inevitable consequence of challenge D1.1 overly conservative margins leading to inefficiencies and D1.4 overuse of margins resulting in environmental and performance costs. Since the product's market success depends on its performance across various criteria, trade offs favoring safety at the expense of performance can significantly impact its competitiveness. This underscores the critical need to identify and capitalize on opportunities to reduce unnecessary margins without compromising safety.

D2.2 Difficulty in determining appropriate margins.

The level of margin is often determined by the acceptable trade off in performance. It is important to consider what the upper limit of a margin would be if no explicit constraints exist within the current functional design area. Margins must balance safety and optimization, not only for the immediate performance metrics but also across subsequent design stages. However, the process for determining the appropriate margin level is not standardized, often resulting in either excessive conservatism or insufficient robustness. This challenge closely relates to D2.3 the difficulty in identifying the right level of margins at different stages, especially when introducing new technologies. For example, determining suitable margins for products manufactured using novel approaches like additive manufacturing can be particularly complex. Coupled with D2.1 the lack of transparency in margin justification,adapting safety margins to new technologies becomes even more challenging.

D3.1 Optimizing design margin strategy for minimum risk.

This challenge centers on finding a carefully calculated compromise between performance and safety, further emphasizing the difficulty highlighted in D2.2 determining appropriate margins. Optimizing margins inherently involves balancing risk to ensure product reliability.

D4.1 Lack of guidance in quantifying the design margins.

There is often no clear framework for assigning and validating design margins, which leads engineers to rely heavily on conservative assumptions. This lack of proactiveness can sometimes be seen as an intentional feature aimed at streamlining communication providing engineers only the essential information needed upfront, while additional details are made available on demand to avoid overwhelming them.

D5.1 Communication gaps in margin data across functions.

This challenge further builds on D4.3 the limited awareness of margin factors across functions. Without a unified margin management platform to facilitate communication, effective coordination becomes impractical. These communication gaps regarding margin data across functions often lead to overcompensation, as similar risks are accounted for multiple times, resulting in the accumulation of redundant margins.

B.1.4 Probabilistic design

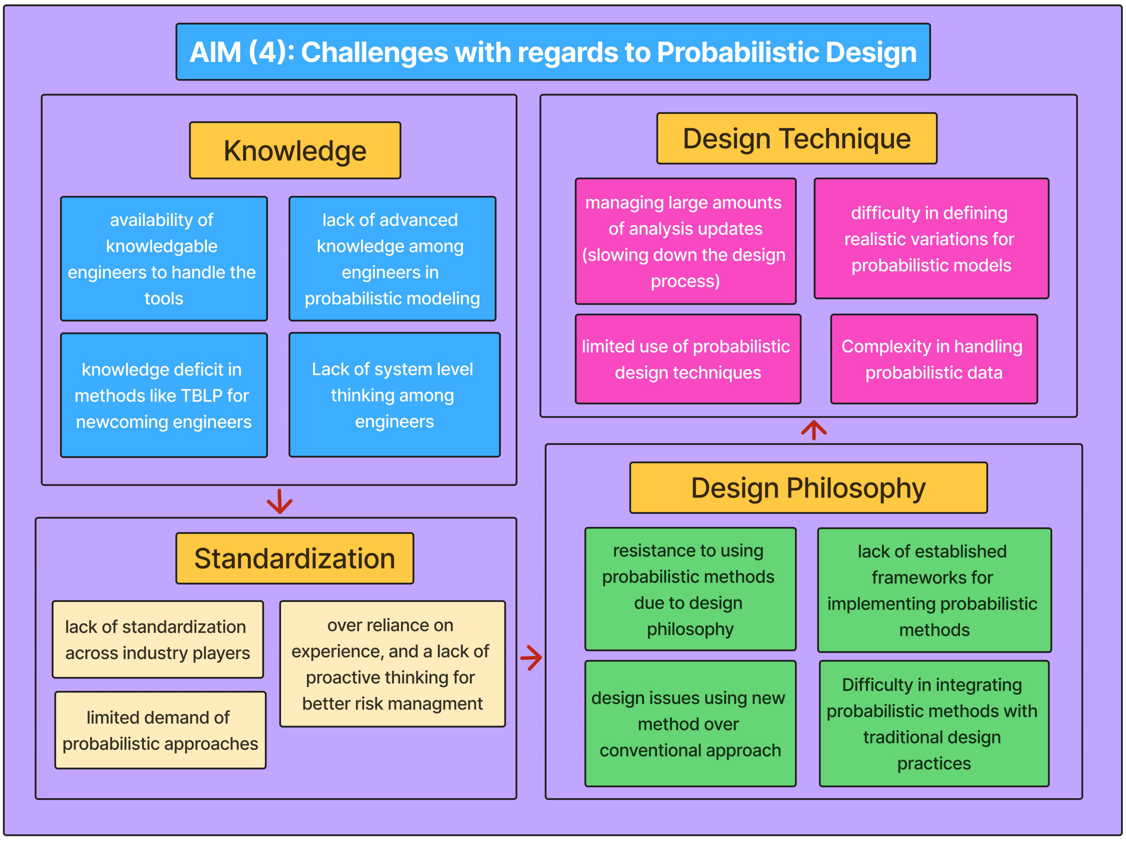


Figure B.4: AIM diagram on probabilistic design

C

Appendix C

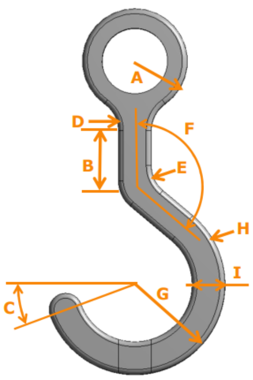
C.1 Quantitative study

C.2 Probabilistic analysis of steel hook

C.2.1 Requirements & initial setup

Objective of minimizing the mass and the maximum stress should not exceed 300 MPa.

Robustness requirement: The optimal design that the failure stress limit stays outside the 4.5 sigma safety margin. Opening width (undeformed) of the lower half circle should be minimum 50 mm in the nominal design [57]



A	Outer_Diameter	28-35 mm
B	Connection_Length	20-50 mm
C	Opening_Angle	10-30 °
D	Upper_Blend_Radius	18-22 mm
E	Lower_Blend_Radius	18-22 mm
F	Connection_Angle	120-150 °
G	Lower_Radius	45-55 mm
H	Fillet_Radius	2-4 mm
I	Thickness	15-25 mm
	Depth	15-25 mm

Figure C.1: Range of geometric parameter

The initial setup in Figure C.2 is considered as the input for the OptiSLang robustness optimization. All the parameterized geometrical dimensions, material properties, and load uncertainties are considered as parameters that are varied in the robustness optimization. The geometric mass, equivalent stress, slipping height, and opening width are considered as the responses. The best design is determined according to the values of the responses on which the constraints are imposed.

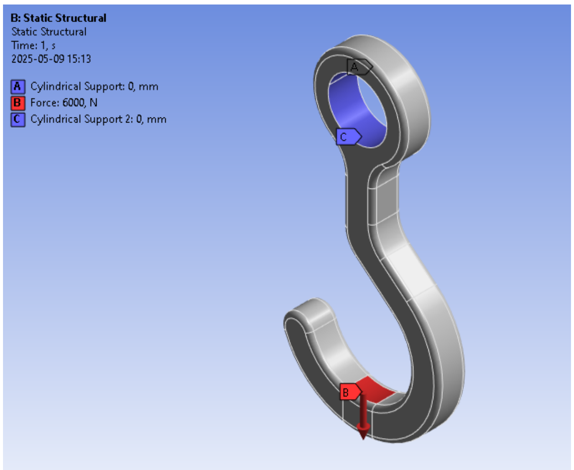
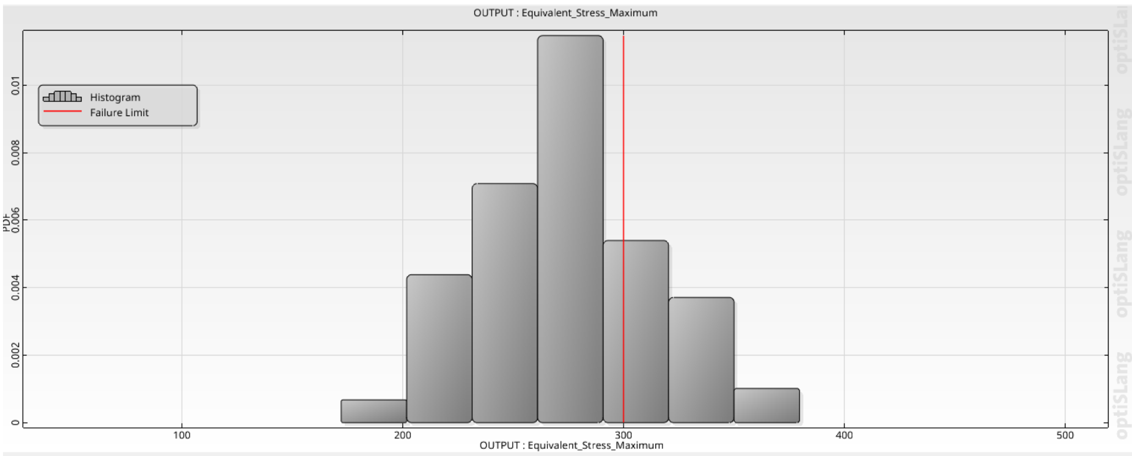


Figure C.2: Boundary Conditions



Hide Statistical data

Statistical data			
Min:	172.173	Max:	379.682
Mean value:	273.764	Standard deviation:	40.5514
CoV:	0.148125		
Skewness:	0.243143	Excess kurtosis:	-0.167105
Limit : Failure Limit			
	Lower value = not set	Upper value = 300	Total
P_rel:		0.21	0.21
Sigma-Level:		0.646984	

Figure C.3: Initial robustness evaluation of hook

C.2.2 Sensitivity analysis

Based on the objective to minimize mass while ensuring the maximum stress does not exceed 300 MPa and with a nominal design constraint that the opening width (undeformed) of the lower half circle must be at least 50 mm, the robustness requirement specifies that the failure stress limit must lie outside a 4.5 sigma safety margin. The initial robustness evaluation, shown in Figure C.3, reveals that the nominal design is non robust, with a sigma level of only 0.646 which is significantly below the required 4.5 sigma and a failure probability of 21 %.

C.3 Steel hook

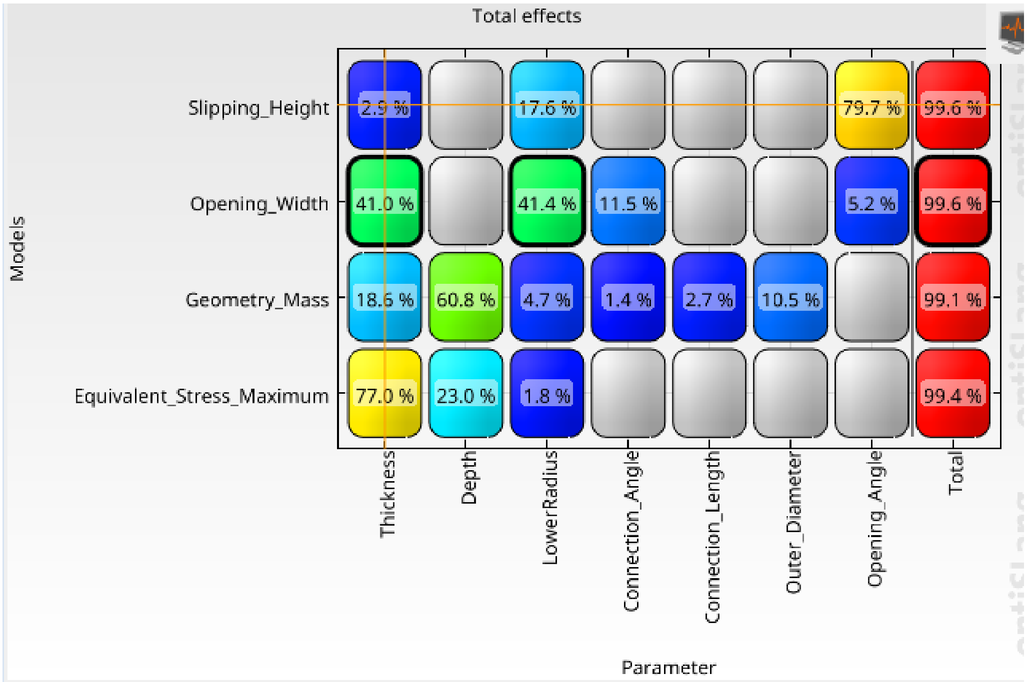


Figure C.4: COP Matrix of steel hook

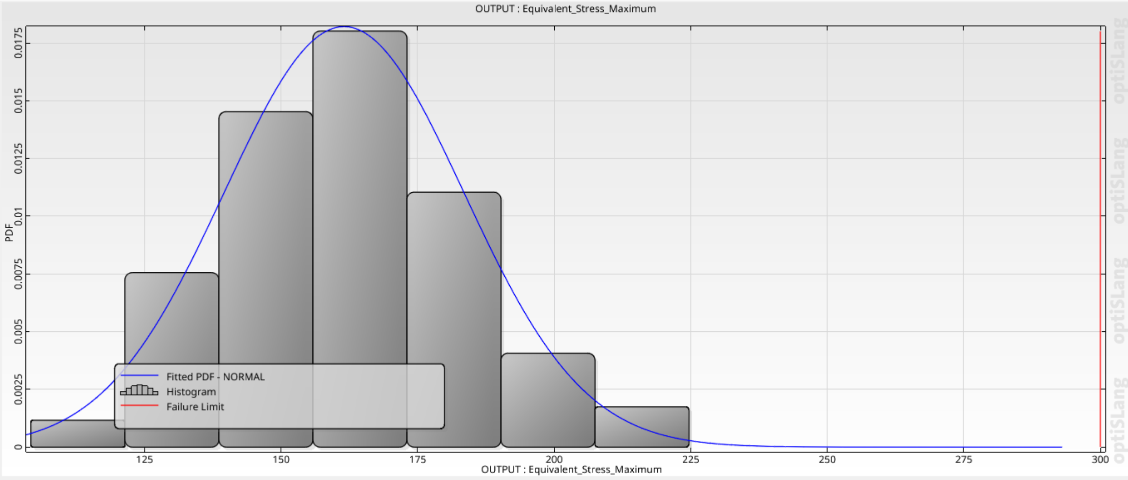
This result prompted further investigation using sensitivity analysis to identify the most influential parameters affecting the responses.

The following insights were gained based sensitivity analysis results from Figure C.4:

1. The mass is mainly influenced by the depth, thickness and outer diameter.
2. The maximum stress is mainly influenced by the depth and thickness.
3. The opening width is mainly influenced by the lower radius and the thickness.
4. Connection length and outer diameter are relevant for the mass with no contribution to the stress value, hence they can be set to minimum values without interference to stress.
5. The parameters of lower and upper blend radi and fillet radius are not important for any response and can be neglected.

C.3.1 Design Optimization

The optimization procedure comprised two cycles: the first cycle targeted a stress criteria of 180 MPa, achieving a reliability index of 3.84 with a failure probability of 10^{-5} and the second cycle targeted 160 MPa (see Figure C.5), resulting in a reliability index of 4.78 and a failure probability of 10^{-7}(see figure C.6).



Hide Statistical data

Statistical data			
Min:	104.194	Max:	224.666
Mean value:	161.525	Standard deviation:	21.9073
CoV:	0.135628		
Skewness:	0.23261	Excess kurtosis:	0.191424
Fitted PDF : NORMAL			
Statistical Moments		Parameter	
Mean value:	161.525	Mean value mu:	161.525
Standard deviation:	21.9073	Standard deviation s:	21.9073
Limit : Failure Limit			
	Lower value = not set	Upper value = 300	Total
P_rel:		0	0
P_fit:		1.29961e-10	1.29961e-10
Sigma-Level:		6.32097	

Figure C.5: Final robustness analysis result of hook

Method : Adaptive Response Surface Method (ARSM)

Complete approximations :	3 / 3
Selected data :	3. Approximation
Probability of Failure :	8.52195e-07
Standard deviation error :	2.05093e-07
Reliability Index :	4.78565
Approximation errors :	R^2 / R^2pred
lim_st_Equivalent_Stress_Maximum:	1 / 0.992413

Figure C.6: Final reliability analysis result of hook

C.3.2 Probabilistic VMEA workflow of hook

A full factorial Design of Experiments (DOE) was conducted on the same model using the prioritized parameters, namely Lower Radius, Fillet Radius, Depth, Thickness . The load parameter of force applied in y direction and material parameters of young's modulus, Poisson's ratio are also considered in the DOE from probabilistic VMEA .The above consideration resulted in the probabilistic VMEA table C.1:

Parameter	Effect	Type of parameter	Min	Max	Max strength	Min strength		Log(max)	Log(min)	Delta
Force_Y_Component	Yes	Load	-6600	-5400	300,44	245,81		5,7052	5,5046	0,0334
Young's_Modulus	No	Material	1,90E+11	2,10E+11	273,11	273,11				
LowerRadius	Yes	Geometric	47	53	258,37	287,88		5,5544	5,6625	0,0180
Poisson's_Ratio	No	Material	0,285	0,315	272,86	273,39		5,6090	5,6109	0,0003
Fillet_Radius	Yes	Geometric	2,4	3,6	267,33	278,92		5,5885	5,6309	0,0071
Depth	Yes	Geometric	17	23	315,97	230,28		5,7556	5,4393	0,0527
Thickness	Yes	Geometric	17	23	351,38	194,87		5,8619	5,2723	0,0983
									Total	0,1180
						Average Equivalent Stress	273,12	5,6099		1,7007
								0,5311		
								5,0789	160,5903	

Table C.1: Probabilistic VMEA table of hook

Parameter	Type	Nominal	Design 1	Design 2	VMEA	Unit
Input	Outer_Diameter	32	28	28	28	mm
	Connection_Length	40	20	20	20	mm
	Connection_Angle	130	131,75	139,55	141,00	degree
	Upper_Blend_Radius	20	20	20	20	mm
	lower_blend_radius	20	20	20	20	mm
	Opening_Angle	20	30	30,00	30	degree
	LowerRadius	**55**	50,29	**49,20**	**49,03**	mm
	Fillet_Radius	**3**	**3**	**3**	**3**	mm
	Thickness	**20**	**25**	**25**	**24,99**	mm
	Depth	**20**	**18,31**	**20,05**	**19,94**	mm
	Factors	**Nominal**	**Design 1**	**Design 2**	**VMEA**	
Output	**Geometric mass**	1,0998	0,8684	0,9585	0,9555	Kg
	Equivalent stress	270	178,668	159,942	160,587	Mpa
	Reliability index	0,646	3,84	**4,78**	**4,77**	Dimensionless
	Faliure probability	21	e-5	**e-7**	**e-7**	Percentage

Table C.2: Design table of hook

The optimization using the 160.59 MPa stress criteria obtained from the new approach, resulted in a design with a maximum equivalent stress of 160.587 MPa, a reliability index of 4.77 and a failure probability of 10^{-7}. As observed in the design table C.2, these design values closely match the best design obtained from the previous two step optimization cycle. Since a similar result was achieved using the probabilistic VMEA approach with fewer optimization cycles, this method offers computational time benefits and was therefore selected for further examination.

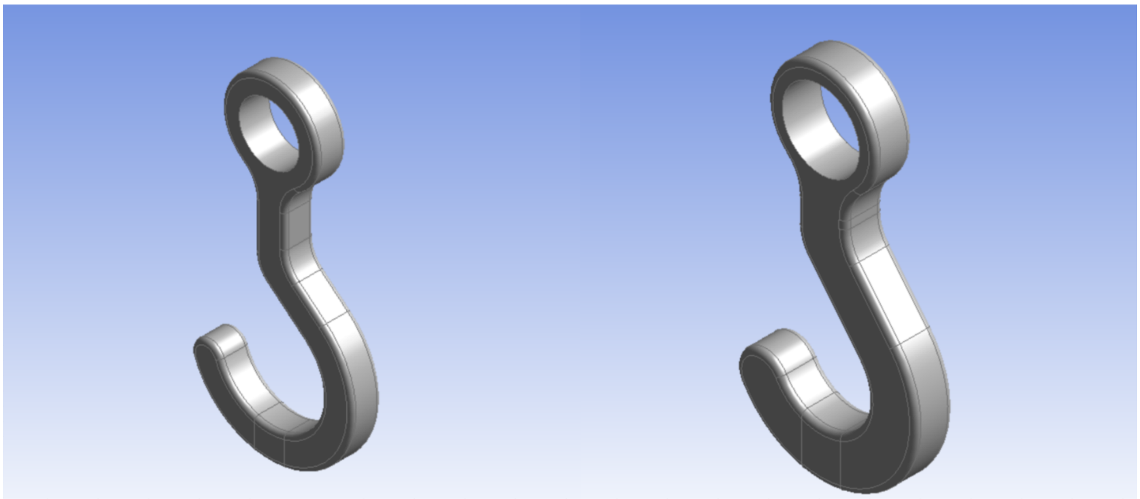


Figure C.7: Geometry of initial hook(left) and optimized hook(right)

C.4 LUG

Geometric parameters

Total_Height	70 mm	Length
Diameter_of_hole	16 mm	Length
Base_Width	50 mm	Length
Top_Width	30 mm	Length
Middle_Angle	45 °	Angle
Large_Fillet_Radius	10 mm	Length
Hole_Vertical_Position	50 mm	Length
Height_of_Base	17 mm	Length
Base_Thickness	20 mm	Length
Top_Thickness	9 mm	Length
Sideprofile_topfillet_rad	10 mm	Length
Half_thickness_layerabove_b...	6 mm	Length
sideprofile_chamfer_angle	70 °	Angle
Sideprofile_Base_Height	12 mm	Length

Figure C.8: Nominal value of parameters of lug

Table C.3: Best design: Sensitivity

Parameter Name	Parameter Value
Base_Thickness	20
Base_Width	44.055
Density	7850
Diameter_of_hole	16.015
Force_Y_Component	9000
Half_thickness_layerabove_base	6.234
Height_of_Base	15.317
Hole_Vertical_Position	49.68
Large_Fillet_Radius	9.11
Middle_Angle	46.665
Poisson's_Ratio	0.3
Sideprofile_Base_Height	9.65
Sideprofile_topfillet_rad	9.15
Top_Thickness	13.125
Top_Width	30.135
Total_Height	68.535
Young's_Modulus	2.00E+11
sideprofile_chamfer_angle	65.31
Equivalent_Stress_Maximum	176.094
Geometry_Mass	0.2412

C.4.1 First Optimization cycle

	Name	Parameter type	Reference value	Constant	Resolution	Range		Range plot	PDF	Type	Mean	Std. Dev.	CoV	Distribution parameter
1	Young's_Modulus	Stochastic	2e+11	☐	Continuous					LOGNORMAL	2e+11	1e+10	5 %	26.0203; 0.0499688
2	Total_Height	Opt.+Stoch.	67.5	☐	Continuous	63	72			NORMAL	67.5	1.5	2.22222 %	67.5; 1.5
3	Top_Width	Opt.+Stoch.	32	☐	Continuous	27	38			NORMAL	32	1.83	5.71875 %	32; 1.83
4	Top_Thickness	Opt.+Stoch.	10.5	☐	Continuous	7	14			NORMAL	10.5	1.16	11.0476 %	10.5; 1.16
5	Sideprofile_topfillet_rad	Opt.+Stoch.	10	☑	Continuous	9	11			NORMAL	10	0.333	3.33 %	10; 0.333
6	sideprofile_chamfer_angle	Opt.+Stoch.	70	☑	Continuous	63	77			NORMAL	70	2.33	3.32857 %	70; 2.33
7	Sideprofile_Base_Height	Opt.+Stoch.	8	☑	Continuous	8	14			NORMAL	8	1	12.5 %	8; 1
8	Poisson's_Ratio	Stochastic	0.3	☐	Continuous					LOGNORMAL	0.3	0.015	5 %	-1.20522; 0.0499688
9	Middle_Angle	Opt.+Stoch.	45	☑	Continuous	40.5	49.5			NORMAL	45	1.5	3.33333 %	45; 1.5
10	Large_Fillet_Radius	Opt.+Stoch.	10	☑	Continuous	9	11			NORMAL	10	0.33	3.3 %	10; 0.33
11	Hole_Vertical_Position	Opt.+Stoch.	47	☐	Continuous	43	51			NORMAL	47	1.333	2.83617 %	47; 1.333
12	Height_of_Base	Opt.+Stoch.	15.3	☑	Continuous	15.3	18.7			NORMAL	15.3	0.56	3.66013 %	15.3; 0.56
13	Half_thickness_layerabove_base	Opt.+Stoch.	5.4	☑	Continuous	5.4	6.6			NORMAL	5.4	0.2	3.7037 %	5.4; 0.2
14	Force_Y_Component	Stochastic	9000	☐	Continuous					NORMAL	9000	900	10 %	9000; 900
15	Diameter_of_hole	Opt.+Stoch.	16.009	☑	Continuous	16	16.0...			NORMAL	16.009	0.003	0.0187395 %	16.009; 0.003
16	Density	Stochastic	7850	☐	Continuous					LOGNORMAL	7850	157	2 %	8.96807; 0.019998
17	Base_Width	Opt.+Stoch.	44	☑	Continuous	44	55			NORMAL	44	1.8333	4.16659 %	44; 1.8333
18	Base_Thickness	Opt.+Stoch.	20	☑	Continuous	15	25			NORMAL	20	1.66	8.3 %	20; 1.66

Figure C.9: Prioritized parameters for optimization of lug

C.4.1.1 Design Optimization I

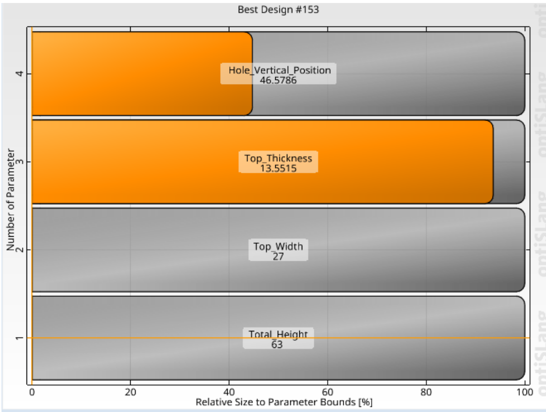


Figure C.10: Values of parameters from optimization I

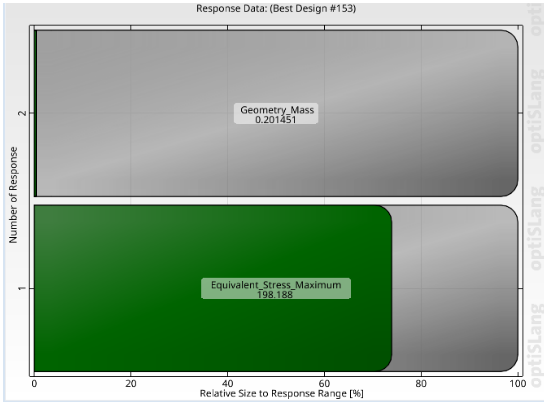
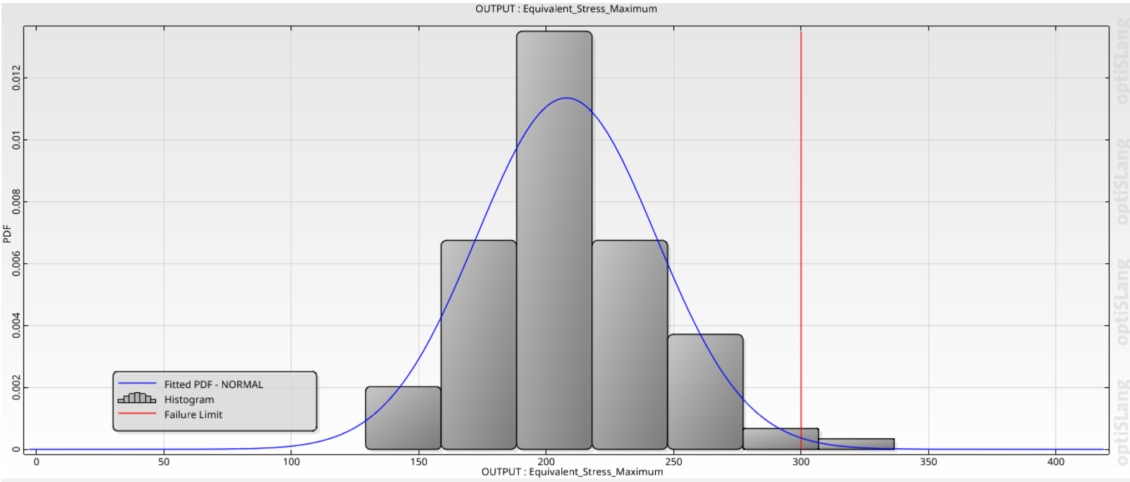


Figure C.11: Values of responses from optimization I

Table C.4: Best design : Optimization 1

Parameter name	Parameter value
Base_Thickness	20
Base_Width	44
Density	7850
Diameter_of_hole	16.009
Force_Y_Component	9000
Half_thickness_layerabove_base	5.4
Height_of_Base	15.3
Hole_Vertical_Position	46.578
Large_Fillet_Radius	10
Middle_Angle	45
Poisson's_Ratio	0.3
Sideprofile_Base_Height	8
Sideprofile_topfillet_rad	10
Top_Thickness	13.551
Top_Width	27
Total_Height	63
Young's_Modulus	2,00E+11
sideprofile_chamfer_angle	70
Equivalent_Stress_Maximum	198.188
Geometry_Mass	0.2014

C.4.1.2 Robustness evaluation and reliability analysis



Hide Statistical data

Statistical data			
Min:	129.134	Max:	336.477
Mean value:	207.911	Standard deviation:	35.1473
CoV:	0.16905		
Skewness:	0.595332	Excess kurtosis:	1.14219
Fitted PDF : NORMAL			
Statistical Moments		Parameter	
Mean value:	207.911	Mean value mu:	207.911
Standard deviation:	35.1473	Standard deviation s:	35.1473
Limit : Failure Limit			
	Lower value = not set	Upper value = 300	Total
P_rel:		0.01	0.01
P_fit:		0.00439534	0.00439534
Sigma-Level:		2.62009	

Figure C.12: Result of robustness analysis I

Method : Adaptive Response Surface Method (ARSM)

Complete approximations : 3 / 3
Selected data : 3. Approximation

Probability of Failure : 0.0207297
Standard deviation error : 0.0018162
Reliability Index : 2.03891

Approximation errors : R^2 / R^2pred
lim_st_Equivalent_Stress_Maximum: 1 / 0.481487

Figure C.13: Result of reliability analysis I

C.4.2 Second Optimization cycle

C.4.2.1 Design Optimization II

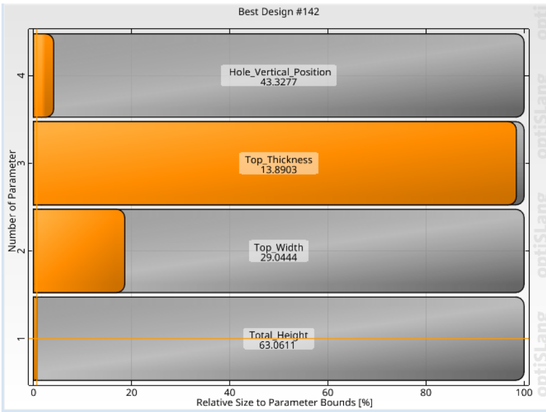


Figure C.14: Values of parameters from optimization II

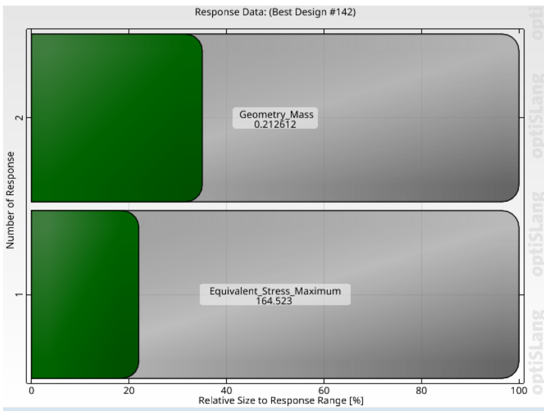
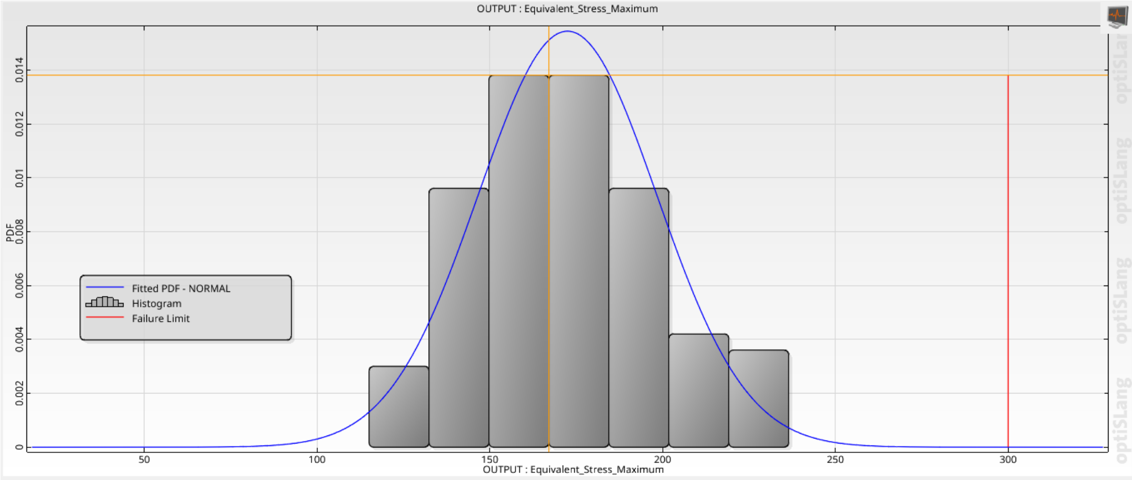


Figure C.15: Values of responses from optimization II

Table C.5: Best design : Optimization II

Parameter name	Parameter value
Base_Thickness	20
Base_Width	44
Density	7850
Diameter_of_hole	16.009
Force_Y_Component	9000
Half_thickness_layerabove_base	5.4
Height_of_Base	15.3
Hole_Vertical_Position	43.327
Large_Fillet_Radius	10
Middle_Angle	45
Poisson's_Ratio	0.3
Sideprofile_Base_Height	8
Sideprofile_topfillet_rad	10
Top_Thickness	13.890
Top_Width	29.044
Total_Height	63.061
Young's_Modulus	2,00E+11
sideprofile_chamfer_angle	70
Equivalent_Stress_Maximum	164.522
Geometry_Mass	0.2126



Hide Statistical data

Statistical data			
Min:	115.075	Max:	236.494
Mean value:	172.483	Standard deviation:	25.8263
CoV:	0.149732		
Skewness:	0.328542	Excess kurtosis:	-0.251855
Fitted PDF : NORMAL			
Statistical Moments		Parameter	
Mean value:	172.483	Mean value mu:	172.483
Standard deviation:	25.8263	Standard deviation s:	25.8263
Limit : Failure Limit			
	Lower value = not set	Upper value = 300	Total
P_rel:		0	0
P_fit:		3.95702e-07	3.95702e-07
Sigma-Level:		4.93748	

Figure C.16: Result of robustness analysis II

Method : Adaptive Response Surface Method (ARSM)

Complete approximations : 3 / 3
Selected data : 3. Approximation

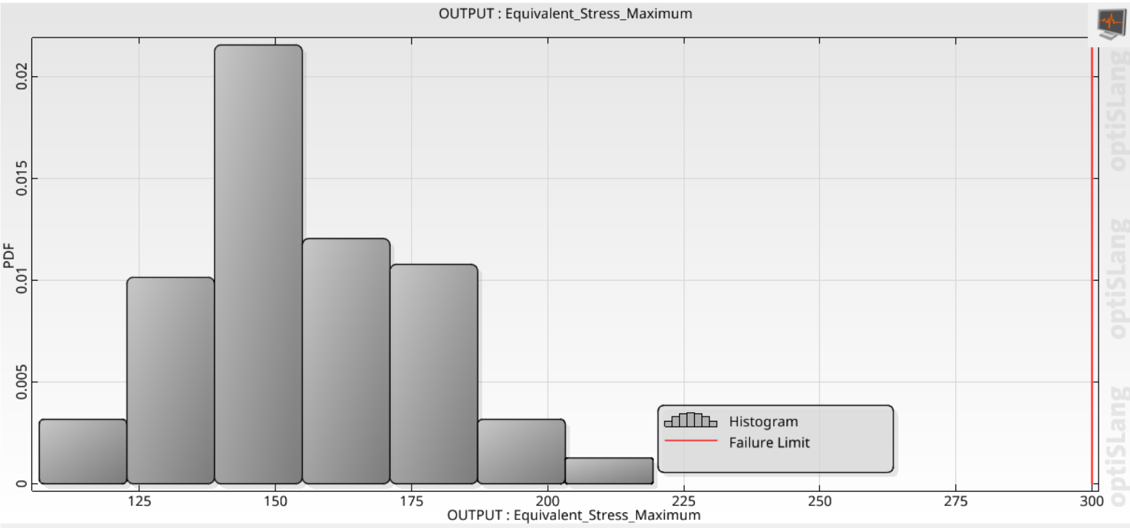
Probability of Failure : 0.000483341
Standard deviation error : 6.42675e-05
Reliability Index : 3.30005

Approximation errors : R² / R²pred
lim_st_Equivalent_Stress_Maximum: 1 / 0.450765

Figure C.17: Result of reliability analysis II

Table C.6: Best design :Optimization III

Parameter name	**Parameter value**
Base_Thickness	20
Base_Width	44
Density	7850
Diameter_of_hole	16.009
Force_Y_Component	9000
Half_thickness_layerabove_base	5.4
Height_of_Base	15.3
Hole_Vertical_Position	43
Large_Fillet_Radius	10
Middle_Angle	45
Poisson's_Ratio	0.3
Sideprofile_Base_Height	8
Sideprofile_topfillet_rad	10
Top_Thickness	13.993
Top_Width	31.104
Total_Height	65.222
Young's_Modulus	2,00E+11
sideprofile_chamfer_angle	70
Equivalent_Stress_Maximum	149.943
Geometry_Mass	0.2298



Hide Statistical data

Statistical data			
Min:	106.595	Max:	219.345
Mean value:	155.259	Standard deviation:	22.3286
CoV:	0.143815		
Skewness:	0.428433	Excess kurtosis:	0.0672065
Limit : Failure Limit			
	Lower value = not set	Upper value = 300	Total
P_rel:		0	0
Sigma-Level:		6.48232	

Figure C.18: Result of robustness analysis with probabilistic VMEA workflow

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